Implicit Neural Representations for Image Compression

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Abstract

Recently Implicit Neural Representations (INRs) gained attention as a novel and effective representation for various data types. Thus far, prior work mostly focused on optimizing their reconstruction performance. This work investigates INRs from a novel perspective, i.e., as a tool for image compression. To this end, we propose the first comprehensive image compression pipeline based on INRs including quantization, quantization-aware retraining and entropy coding. Encoding with INRs, i.e., overfitting to a data sample, is typically orders of magnitude slower. To mitigate this drawback, we leverage meta-learned initializations based on MAML to reach the encoding in fewer gradient updates which also generally improves rate-distortion performance of INRs. We find that our approach to source compression with INRs vastly outperforms similar prior work, is competitive with common compression algorithms designed specifically for images and closes the gap to state-of-the-art learned approaches based on Rate-Distortion Autoencoders. Moreover, we provide an extensive ablation study on the importance of individual components of our method which we hope facilitates future research on this novel approach to image compression.

1. Introduction

Living in a world where digitalization is ubiquitous and important decisions are based on big data analytics, the problem of how to store information effectively is more important than ever. Source compression is the generalized term for representing data in a compact form, that either preserves all the information (lossless compression) or sacrifices some information for even smaller file sizes (lossy compression). It is a key component to tackle the flood of image and video data that is uploaded, transmitted and downloaded from the internet every day. While lossless compression is arguably more desirable, it has a fundamental theoretical limit, namely Shannon’s entropy [44]. Therefore, lossy compression aims at trading off a file’s quality with its size - called rate-distortion trade-off.

Apart from traditional hand-designed algorithms tuned for particular data modalities, e.g. audio, images or video, machine learning research has recently developed promising learned approaches to source compression by leveraging the power of neural networks. Such methods typically build on the well-known autoencoder [25] by implementing a constrained version of it. These so-called Rate-Distortion Autoencoders (RDAEs) [5, 6, 22, 34] jointly optimize the
quality of the decoded data sample and its encoded file size. This work sidesteps the prevalent approach of RDAEs and investigates a novel paradigm for source compression—particularly focusing on image compression. Recently, Implicit Neural Representations (INRs) gained popularity as a flexible, multi-purpose data representation that is able to produce high-fidelity samples on images [46], 3D shapes [41, 46] and scenes [37]. In general, INRs represent data that lives on an underlying regular grid by learning a mapping between the grid’s coordinates and the corresponding data values (e.g. RGB values) and have even been hypothesized to yield well compressed representations [46]. Consequently, a naturally arising question is: How good are these INRs in terms of rate-distortion performance? However, to this date INRs have been surprisingly absent from research on source compression. To the best of our knowledge, only COIN [17] and the concurrent NeRV [10] considers INRs to compress images, resp. videos.

We hypothesize that there are two main reasons why INRs have not been applied to image compression. (1) Straightforward approaches struggle to compete even with the simplest traditional algorithms [17]. (2) Since INRs encode data by overfitting to particular instances, the encoding time is perceived impractical. To this end, we propose a comprehensive image compression pipeline on the basis on INRs. While we focus on images, we emphasize that our proposed method can easily be adapted to any coordinate-based data modality. We show that our pipeline vastly outperforms the recently proposed COIN [17] and is competitive with traditional compression algorithms for images. Our extensive ablation study reveals that the young field of INRs-based compression can greatly improve by making targeted choices regarding the neural network architecture. Furthermore, we exploit recent advances in meta-learning for INRs [45, 48] based on Model-Agnostic Meta-Learning (MAML) [19] to find weight initializations that can compress data with fewer gradient updates as well as yield better rate-distortion performance. We show that utilizing existing MAML implementations for INRs, which are not specialized in compression, yields strong improvements in rate-distortion performance, in particular on distributions of less variability. Overall, we manifest that INRs are a promising emerging compression paradigm that can already compete with traditional algorithms and primarily requires deriving architectures for INRs and meta-learning approaches tailored to compression needs.

2. Related Work

Learned Image Compression. The modern era in learned image compression was introduced in [6] by proposing an end-to-end autoencoder and entropy model that jointly optimizes rate and distortion. In the following, [7] extends this approach by adding a scale hyperprior, and then [30, 34, 38] propose employing autoregressive entropy models to further improve the compression performance. Later, Hu et al. [26] propose a coarse-to-fine hierarchical hyperprior, and Cheng et al. [13] achieve further improvements by adding attention modules and using a Gaussian Mixture Model (GMM) to estimate the distribution of latent representations. The current state-of-the-art is achieved by [55]: They propose an invertible convolutional network, and apply residual feature enhancement as pre-processing and post-processing. Moreover, there are also plenty of methods aiming at variable rate compression, mainly including RNN-based autoencoders [27, 50, 51] and conditional autoencoders [14]. Besides, [4, 35] propose image compression with Generative Adversarial Networks (GAN) to optimize perceptual quality.

Implicit Neural Representations. One of the early works on INRs is DeepSDF [42] which is a neural network representation for 3D shapes. In particular, they use a Signed Distance Function (SDF) to represent the shape by a field where every point in space holds the distance to the shape’s surface. Concurrently to DeepSDF, multiple works propose similar approaches to represent 3D shapes with INRs, e.g., the occupancy network [36] and the implicit field decoder [12]. Besides, INRs have also been used for scene representation [37], image representation [11, 47] and compact representation [15].

Model Compression. In the past decades, there has been a plethora of works on model compression [33]. For instance, [23] proposes sequentially applying pruning, quantization and entropy coding combined with retraining in between the steps. Later, [2] suggests an end-to-end learning approach using a rate-distortion objective. To optimize performance under quantization, several works [16, 21, 52, 54] use mixed-precision quantization, while others [9, 18, 28, 32, 39, 40] propose post-quantization optimization techniques.

Model Weights for Instance-Adaptive Compression. Recently, [53] suggests finetuning the decoder weights of an RDAE on a per-instance basis and appending the weight update to the latent vector, thereby improving RDAEs. It is related to our work in that model weights are included in the representation, however the RDAE architecture fundamentally differs from ours. Most recently, Dupont et al. [17] propose the first INR-based image compression approach COIN, which overfits an INR’s model weights to represent single images and compresses the INR using quantization. Importantly, COIN does not use post-quantization retraining, entropy coding and meta-learning for initializing INRs. Moreover, concurrently NeRV [10] proposed to compress videos using INRs. While they use another data modality and neither use post-quantization retraining nor meta-
learned initializations, we value the growing interest in the young field of INRs-based source compression.

3. Method

3.1. Background

INRs store coordinate-based data such as images, videos and 3D shapes by representing data as a continuous function from coordinates to values. For example, an image is a function of a horizontal and vertical coordinate \((p_x, p_y)\) and maps to a color vector within a color space such as RGB:

\[
I: (p_x, p_y) \rightarrow (R, G, B)
\]  

(1)

This mapping can be approximated by a neural network \(f_\theta\), typically a Multi Layer Perceptron (MLP) with parameters \(\theta\), such that \(I(p_x, p_y) \approx f_\theta(p_x, p_y)\). Since these functions are continuous, INRs are resolution agnostic, i.e., they can be evaluated on arbitrary coordinates within the normalized range \([-1, 1]\). To express a pixel based image tensor \(\mathbf{x}\), we evaluate the image function on a uniformly spaced coordinate grid \(\mathbf{p}\) such that \(\mathbf{x} = I(\mathbf{p}) \in \mathbb{R}^{W \times H \times 3}\) with

\[
\mathbf{p}_i = \left(\frac{2i}{W-1} - 1, \frac{2j}{H-1} - 1 \right) \in [-1, 1]^2 \quad \forall i \in \{0, \ldots, W - 1\}, j \in \{0, \ldots, H - 1\}
\]  

(2)

Note that each coordinate vector is mapped independently:

\[
f_\theta(\mathbf{p}) = \begin{bmatrix}
f_\theta(\mathbf{p}_{11}) & \cdots & f_\theta(\mathbf{p}_{1H}) \\
\vdots & \ddots & \vdots \\
f_\theta(\mathbf{p}_{W1}) & \cdots & f_\theta(\mathbf{p}_{WH})
\end{bmatrix}.
\]  

(3)

Rate-distortion Autoencoders. The predominant approach in learned source compression are RDAEs: An encoder network produces a compressed representation, typically called a latent vector \(\mathbf{z} \in \mathbb{R}^d\), which a jointly trained decoder network uses to reconstruct the original input. Early approaches enforce compactness of \(\mathbf{z}\) by limiting its dimension \(d\) [24]. Newer methods constrain the representation by adding an entropy estimate, the so-called rate loss, of \(\mathbf{z}\) to the loss. This rate term, reflecting the storage requirement of \(\mathbf{z}\), is minimized jointly with a distortion term, that quantifies the compression error.

3.2. Image Compression using INRs

In contrast to RDAEs, INRs store all information implicitly in the network weights \(\theta\). The input to the INR itself, i.e. the coordinate, does not contain any information. The encoding process is equivalent to training the INR. The decoding process is equivalent to loading a set of weights into the network and evaluating on a coordinate grid. We can summarize this as:

\[
\arg \min_\theta \mathcal{L}(\mathbf{x}, f_\theta(\mathbf{p})) = \theta^* \xrightarrow{\text{transmit } \theta^*} \hat{\mathbf{x}} = f_{\theta^*}(\mathbf{p}) \quad (4)
\]

Thus, we only need to store \(\theta^*\) to reconstruct a distorted version of the original image \(\mathbf{x}\). With our approach, we describe a method to find \(\theta^*\) to achieve compact storage and good reconstruction at the same time.

Architectures. We use SIREN, namely a MLP using sine activations with a frequency \(\omega = 30\) as proposed originally in [46], which has recently shown good performance on image data. We adopt the initialization scheme suggested by the authors. Since we aim to evaluate our method at multiple bitrates, we vary the model size to obtain a rate-distortion curve. We also provide an ablation on how to vary the model size to achieve optimal rate-distortion performance (see Section 4.4) and on the architecture of the INR (see Section 4.5).

Input Encoding. An input encoding transforms the input coordinate to a higher dimension, which has been shown to improve perceptual quality [37, 49]. Notably, to the best of our knowledge we are the first to combine SIREN with an input encoding - previously input encodings have only been used for INRs based on the Rectified Linear Unit (ReLU) activation functions. We apply an adapted version of the positional encoding presented in [37], where we introduce the scale parameter \(\sigma\) to adjust the frequency spacing (similarly to [49]) and concatenate the frequency terms with the original coordinate \(p\) (as in the codebase for SIREN )1:

\[
\gamma(p) = (p, \sin(\sigma^0 \pi p), \cos(\sigma^0 \pi p), \ldots, \\
\quad \sin(\sigma^{L-1} \pi p), \cos(\sigma^{L-1} \pi p)).
\]  

(5)

where \(L\) is the number of frequencies used. We investigate the impact of the input encoding in Section 4.5.

3.3. Compression Pipeline for INRs

This section introduces our INR-based compression pipeline. First, we describe our core/basic approach based on randomly initialized INRs (Section 3.3.1). Subsequently, we propose meta-learned initializations to improve INR-based compression in terms of rate-distortion performance and encoding time (Section 3.3.2). The combined compression pipeline is depicted in Fig. 2 and a higher level overview is shown in Fig. 1.

3.3.1 Basic Approach using Random Initialization

Stage 1: Overfitting. First, we overfit the INR \(f_\theta\) to a data sample. The overfitting takes place at test time and is equivalent to calling the encoder of other learned methods. We call this step overfitting to emphasize that the INR is

1https://github.com/vsitzmann/siren
trained to only represent a single image. Given an image \( x \) and a coordinate grid \( p \), we minimize the objective:

\[
\arg \min_{\theta} \mathcal{L}_{\text{MSE}}(x, f_\theta(p)).
\]  

(6)

We use the Mean Squared Error (MSE) as the loss function to measure similarity of the ground-truth target and the INRs output:

\[
\mathcal{L}_{\text{MSE}}(x, \hat{x}) = \sum_{i}^{W} \sum_{j}^{H} \frac{\| x_{ij} - \hat{x}_{ij} \|_2^2}{WH}.
\]  

(7)

Note that \( x_{ij} \in \mathbb{R}^3 \) is the color vector of a single pixel.

**Regularization.** In image compression, we aim at minimizing distortion (e.g., MSE) as well as bitrate simultaneously. Since the model entropy is not differentiable, we can not directly use it in gradient-based optimization. One option that has been used in literature is to use a differentiable entropy estimator during training [2]. We however choose to use a regularization term that approximately induces lower entropy. In particular, we apply \( L_1 \) regularization to the model weights. Overall, this yields the following optimization objective:

\[
\mathcal{L}(x, f_\theta(p)) = \mathcal{L}_{\text{MSE}}(x, f_\theta(p)) + \lambda \|\theta\|_1
\]  

(8)

where \( \lambda \) determines the importance of the \( L_1 \) regularization. The \( L_1 \) loss has the property of inducing sparsity. Our regularization term is thus related to the sparsity loss employed in [33]: we have the same goal of limiting the entropy of the weights, however we apply this to an INR, whereas they apply it to a traditional explicit decoder.

**Stage 2: Quantization.** Typically, the model weights resulting from overfitting are single precision floating point numbers requiring 32 bits per weight. To reduce the memory requirement, we quantize the weights using the AI Model Efficiency Toolkit (AIMET)\(^1\). We employ quantization specific to each weight tensor such that the uniformly-spaced quantization grid is adjusted to the value range of the tensor. The bitwidth determines the number of discrete levels, i.e., quantization bins. We find empirically that bitwidths in the range of 7-8 lead to optimal rate-distortion performance for our models as shown in the supplement.

**Stage 3: Post-Quantization Optimization.** Quantization reduces the models performance by rounding the weights to their nearest quantization bin. We leverage two methods to mitigate this effect. First, we employ AdaRound [39], which is a second-order optimization method to decide whether to round a weight up or down. The core idea is that the traditional nearest rounding is not always the best choice, as shown in [39]. Subsequently, we fine-tune the quantized weights using Quantization Aware Training (QAT). This step aims to reverse part of the quantization error. Quantization is non-differentiable and we thus rely on the Straight Through Estimator (STE) [8] for the gradient computation, essentially bypassing the quantization operation during backpropagation.

**Stage 4: Entropy Coding.** Finally, we perform entropy coding to further losslessly compress weights. In particular, we use a binarized arithmetic coding algorithm to losslessly compress the quantized weights.

3.3.2 Meta-learned Initializations for Compressing INRs

Directly applying INRs to compression has two severe limitations: firstly, it requires overfitting a model from scratch to a data sample during the encoding step. Secondly, it does not allow embedding inductive biases into the compression algorithm (e.g., knowledge of a particular image distribution). To this end, we apply meta-learning, i.e. Model Agnostic Meta-Learning (MAML) [20], for learning a weight initialization that is close to the weight values and entails information of the distribution of images. Previous work on meta-learning for INRs has aimed at improving mainly convergence speed [48]. The learned initialization \( \theta_0 \) is claimed to be closer in weight space to the final INR. We want to exploit this fact for compression under the hypothesis that the update \( \Delta \theta = \theta - \theta_0 \) requires less storage than the full weight tensor \( \theta \). We thus fix \( \theta_0 \) and include it in the decoder such that it is sufficient to transmit \( \Delta \theta \), or, to be precise, the quantized update \( \Delta \tilde{\theta} \). The decoder can then reconstruct the image by computing:

\[
\tilde{\theta} = \theta_0 + \Delta \tilde{\theta}, \quad \tilde{x} = f_{\tilde{\theta}}(p).
\]  

(9)

We expect the interval of values occupied by the weight updates \( \Delta \theta \) to be significantly smaller than that of the full weights \( \theta \). The range between the lowest and highest quantization bin can thus be smaller when quantizing the weight updates. If we compare at a fixed bitwidth, the stepsize in-between bins will be lower for quantizing the weight updates, thus, the average rounding error is also smaller.

Note that the learning of the initialization is only performed once per distribution \( D \) prior to overfitting a single image. Thus, we introduce it as Stage 0. Stage 0 happens at training time, is performed on many images and is not part of inference. Stages 1-4 happen at inference time and aim at compressing a single image. Consequently, using meta-learned initializations does not increase inference time.

\(^1\)https://quic.github.io/
Integration into a Compression Pipeline. When we want to encode only the update $\Delta \theta$, we need to adjust our compression pipeline accordingly. During overfitting we change the objective to:

$$\mathcal{L}(x, f_b(p)) = \mathcal{L}_{MSE}(x, f_b(p)) + \lambda \|\Delta \theta\|_1$$

Thus, the regularization term now induces the model weights to stay close to the initialization. Also, we directly apply quantization to the update $\Delta \theta$. In order to perform AdaRound and QAT, we apply a decomposition to all linear layers in the MLP to separate initial values from the update:

$$Wx + b = (W_0 + \Delta W)x + (b_0 + \Delta b) = (W_{0x} + b_0) + (\Delta Wx + \Delta b).$$

This is necessary, because optimizing the rounding and QAT require the original input-output function of each linear layer. Splitting it up into two parallel linear layers, we can fix the linear layer containing $W_0$ and $b_0$ and apply quantization, AdaRound and QAT to the update parameters $\Delta W$ and $\Delta b$.

4. Experiments

Datasets. The Kodak [1] dataset is a collection of 24 images containing various objects, people or landscapes. This dataset has a resolution of $768 \times 512$ pixels (vertical $\times$ horizontal). The DIV2K dataset introduced in [3] contains 1000 high resolution images with a width of $\approx 2000$ pixels. The dataset is split into 800 training, 100 validation and 100 test images. For our purpose of meta-learning the initialization, we resize the DIV2K images to the same resolution as Kodak ($768 \times 512$). CelebA [31] is a dataset containing over 200'000 images of celebrities with a resolution of $178 \times 218$. We evaluate our method on 100 images that are randomly sampled from the test set.

Metrics. We evaluate two metrics to analyze performance in terms of rate and distortion. We measure the rate as the total number of bits required to store the representation divided by the number of pixels $W \cdot H$ of the image:

$$\text{bitrate} = \frac{\text{total number of bits}}{WH} \quad \text{[bpp]}. \quad (12)$$

We measure distortion in terms of MSE and convert it to the Peak Signal to Noise Ratio (PSNR) using the formula:

$$\text{PSNR} = 10 \log_{10} \left( \frac{1}{\text{MSE}} \right) \quad \text{[dB]}.
\quad (13)$$

Baselines. We compare our method against traditional codecs, INR based compression and learned approaches based on RDAEs.

- Traditional codecs: JPEG, JPEG2000, BPG
- INR-based: Dupont et al. [17] (COIN)
- RDAE-based: Ballé et al. [6], Xie et al. [55]

Optimization and Hyperparameters. We use a default set of hyperparameters throughout the experiment section unless mentioned otherwise. In particular, we use INRs with 3 hidden layers and sine activations combined with the positional encoding using $\sigma = 1.4$. On the higher resolution Kodak dataset, we set the number of frequencies to $L = 16$, whereas on CelebA we set $L = 12$. We vary the number of hidden units per layer $M$, i.e. the width of the MLP, to evaluate performance at different rate-distortion operating points. For CelebA images we choose $M \in \{24, 32, 48, 64\}$ and for Kodak images we choose $M \in \{32, 48, 64, 128\}$. The regularization parameter is $\lambda = 10^{-5}$ as default. We refer to our method with random initialization as the basic approach whereas the method including meta-learned initialization is called meta-learned. We found the optimal bitwidth to be $b = 7$ for the meta-learned approach and $b = 8$ for the basic approach. We determined the hyperparameters by performing a grid search and choosing a value that works best at different bitrates. We implement our method in PyTorch [43] and train the INRs using Adam [29] during overfitting and QAT. We use mixed precision training to reduce the memory requirement and improve training speed. In general, the results shown are obtained using AdaRound and QAT combined. We refer to the supplementary material for additional training details. Since we change the axis scaling between experiments, we include the JPEG and JPEG2000 baselines in all plots to provide a reference.
4.1. Comparison with State-of-the-Art

For this section we train with default hyperparameters resulting in our best performing models for the basic approach and the meta-learned approach.

Fig. 3 and Fig. 4 depict our results on Kodak/CelebA respectively. The proposed basic approach can already outperform COIN clearly over the whole range of bitrates. It is also better than JPEG for most bitrates, except the highest setting on CelebA. With our proposed meta-learned approach we improve over the basic approach at all bitrates. Between the two datasets, the difference is noticeably greater on the CelebA dataset. At the lowest bitrate examined the meta-learned approach reaches the performance of JPEG2000, however our approach cannot keep up with JPEG2000 at higher bitrates. On the CelebA dataset, the meta-learned approach also almost reaches the performance of an autoencoder with a factorized prior [6] at lower bitrates. Towards higher bitrates, the advantage of the autoencoder becomes clearer. BPG as well as the state-of-the-art RDAE [55] clearly outperform our method on both datasets.

4.2. Visual Comparison to JPEG and JPEG2000

We compare compressed images of our meta-learned approach with the codecs JPEG and JPEG2000 in Fig. 6 (Kodak) and Fig. 7 (CelebA). We visually confirm that our model significantly improves over JPEG: Our model produces an overall more pleasing image with better detail and less artifacts although we operate at a lower bitrate on both images. For the Kodak image in Fig. 6 we achieve a slightly lower bitrate at the same distortion compared to JPEG2000. Visually, the JPEG2000 image shows more artifacts around edges and in regions with high frequency details. The sky is however rendered better on the JPEG2000 image because our model introduces periodic artifacts. For the CelebA image in Fig. 7 our method achieves a lower bitrate and higher PSNR than the JPEG2000 image. JPEG2000 again shows artifacts around edges (for example around the letters in the background) and smooths out transitions from lighter to darker areas on the face. Our method produces a more natural tonal transition.

4.3. Convergence Speed

In Fig. 5 we show how the basic and meta-learned approach compare over different numbers of epochs. Especially in the beginning of the overfitting, the meta-learned approach shows significantly faster convergence. Already after the first 3 epochs, we obtain better performance than what the basic approach achieves after 50 epochs. Convergence slows down as we approach the final performance of the respective model, while the meta-learned approach maintains the advantage: It achieves the same performance after 2500 epochs as the basic approach after 25000 epochs. This amounts to a reduction in training time of 90%.

4.4. Number of Layers and Hidden Dimension

Important architecture choices when using MLP based networks, are the number of hidden layers and the num-
Figure 6. Visual comparison of images compressed with JPEG (quality factor 1), JPEG2000 (compression factor 287) and our meta-learned approach. We use a model with a hidden dimension of $M = 32$. JPEG introduces heavy block artifacts and loss of color information resulting in the worst image in comparison. JPEG2000 shows blurring and blocking around edges. Our method maintains better local contrast but shows periodic artifacts visible in the sky as well as smearing at some edges.

Figure 7. Visual comparison of images compressed with JPEG (quality factor 13), JPEG2000 (compression factor 47) and our proposed method using meta-learning evaluated on a CelebA image using a hidden dimension of $M = 24$. Our method renders the most natural image overall, preserving tonal transitions that are smoothed out in the JPEG2000 result. JPEG suffers from strong blocking artifacts, which are also slightly visible in the background detail of the JPEG2000 result.

An important architecture choice is the combination of hidden units. Given an MLP, depth or width both directly influence the number of parameters and indirectly impact bitrate. In other words, there are two ways of scaling up the network. We examine the rate-distortion performance for various combinations of hidden units ($M \in \{32, 48, 64, 96, 128\}$) and hidden layers ($\{2, \ldots, 8\}$) in Fig. 8 using our basic approach and $\lambda = 10^{-6}$. We can see from both plots that increasing the number of layers eventually leads to diminishing returns: The bitrate keeps increasing while the gain in PSNR is small. The flattening for higher numbers of hidden layers is even more pronounced at the lower bitwidth $b = 7$. The quantization noise is stronger here and with increasing depth the noise might get amplified and limit the performance. We conclude that rate-distortion performance scales more gracefully with respect to the width of the model.

Figure 8. Comparing compression performance of models with the number of hidden layers (hl) varying between 2-8 and quantization bitwidths of $b = 7$ or $b = 8$ bits.

Figure 9. Rate-distortion performance of different combinations of input encoding and activation function on the Kodak dataset.

4.5. Choosing Input Encoding and Activation

An important architecture choice is the combination of input encoding and the activation function used. We compare against the Gaussian encoding proposed in [49]. For this encoding we use the same number of frequencies as hidden dimensions ($L = M$) as in [49] and a standard deviation of $\sigma = 4$. We train models with different hidden dimensions ($M \in \{32, 48, 64, 96, 128\}$) and different input encodings on the Kodak dataset starting from random initializations using the regularization parameter $\lambda = 10^{-6}$. 
Looking at Fig. 9a, compared to Fig. 9b we can see that the sine activation outperforms the ReLU activation in every configuration, especially at higher bitrates. The best overall input encoding is positional encoding beating Gaussian for both activations. The MLP without input encoding and sine activations, the SIREN architecture, performs significantly better than its ReLU counterpart but still cannot reach the performance of the models with input encoding.

4.6. Impact of $L_1$ Regularization.

In this experiment we try to verify whether $L_1$ regularization has a beneficial effect on performance. We train with the default parameters starting from random initializations and vary $\lambda$ within $[0, 10^{-4}]$.

We observe that for both datasets a value of $\lambda = 10^{-5}$ has better performance at higher bitrates than lower choices for $\lambda$. The performance improvement shows as a reduction in bitrate which supports the claim that the $L_1$ regularization can lead to a reduction in entropy. Increasing, the regularization strength to $\lambda = 10^{-4}$ restricts the weights too much, resulting in worse performance than $\lambda = 10^{-5}$. Thus, $L_1$ regularization can help to reduce entropy, but needs to be combined with a modification in architecture size to achieve a good rate-distortion tradeoff.

4.7. Post-Quantization Optimization.

We compare our meta-learned approach for different post-quantization optimization settings. Fig. 11 shows the performance difference evaluated on Kodak. We see that AdaRound and retraining applied on their own lead to a consistent improvement. The best choice throughout the bitrate range is however to apply the methods in conjunction.

5. Conclusion

Overall, INRs demonstrated potential to being used as a compressed representation for images. We achieve a large improvement in terms of rate-distortion performance over previous methods [17] performing image compression based on INRs. Performance gains can be particularly attributed to a careful ablation of the INR architecture and the introduction of meta-learned initializations. Moreover, our approach is the first that allows INRs to be competitive with traditional codecs over a large portion of bitrates.

We emphasize that our proposed meta-learning approach has shown a significant advantage over the basic approach with random initializations. Specifically, we observed a reduction in bitrate at the same reconstruction quality. Thus, we can use a lower quantization bitwidth while maintaining a similar PSNR. This supports the hypothesis that the weight updates are more compressible than the full model weights. In particular, the performance gain is more prominent on the CelebA dataset, where the initializations are trained on an image distribution that is more similar to the test set. Moreover, the distribution of celebrity faces has also less variation than the distribution of natural scenes which potentially eases the learning of a single strong initialization. Consequently, we can make our compression algorithm adaptive to a certain distribution by including a priori knowledge into the initialization.

Moreover, the introduction of meta-learned initializations to INR-based compression is a potential solution for long encoding times: We show that our meta-learned approach can reduce training time by up to 90% while achieving the same performance as the basic approach.

We also highlight the importance of the architecture and input encodings for INR-based compression (see Fig. 9). This demonstrates significance of choosing the correct inductive biases for compression and is another promising future research avenue.

A clear limitation that necessarily needs to be addressed by future work is the scaling of INRs to higher bitrates. While we observed that scaling the hidden dimension improves scaling properties in terms of rate-distortion performance (see Fig. 8), compared to existing methods, INR-based methods (ours and COIN [17]) consistently show less competitive performance at higher bitrates. Thus, it is crucial to develop new architectures for INRs beyond the MLP.
that mitigate the current deficits at high bitrates.

While INR-based compression - e.g. ours and COIN for image compression and NeRV for video compression - does not outperform RDAE-based methods, it is arguably still in its infancy. However, we have shown that a carefully constructed compression pipeline elevates INR-based methods to the range of some traditional algorithms and meta-learning's potential for eradicating long encoding times.

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6. Supplementary Material

In Section 6.1 we provide a description of the meta-learning algorithm and in Section 6.2 we explain in detail how we overfit starting from meta-learned initializations. In Section 6.3 we present a complete overview of the hyperparameters used in the different stages of the compression pipeline. Additional ablation studies on the influence of quantization bitwidth and the generalization potential of meta-learned initializations are shown in Section 6.4 and Section 6.5 respectively. Finally, we provide additional qualitative examples comparing our method to JPEG and JPEG2000 in Section 6.6.

6.1. Meta-Learning Algorithm

Meta-learned Initializations for Implicit Neural Representations  Algorithm 1 is an adapted version of the algorithm presented in [45]. We modify the notation to match ours and change the objective to image regression instead of signed distance function regression. Generally, the algorithm consists of two loops, the outer loop (lines 7-15) and the inner loop (lines 11-13). The outer loop index $i$ is denoted as a superscript, whereas the inner loop index $j$ is denoted as a subscript. The outer loop is executed for a pre-defined number of iterations $n$. First of all, we sample an image $x^i$ from the data distribution. We then define a coordinate vector $p$ with a coordinate grid of the same resolution as the image $x^i$. We initialize the inner loop parameters $\phi_0^i$ to the current outer loop parameters $\theta$. For $i = 1$ this is just random initialization, afterwards these are the meta-learned parameters. We start the inner loop on line 9. For $k$ iterations we compute the MSE loss between the image $x^i$ and the output of the INR parameterized by the inner loop parameters $\phi_j^i$. On line 13 we perform a gradient update of the inner loop parameters $\alpha$. The learning rates $\alpha$ contains the learning rates for the inner loop gradient update. A simple choice is using the same static learning rate for all parameters in $\phi_j^i$. The power of meta-learning is that we can also meta-learn the learning rate of the inner loop, thus $\alpha$ is an optimization variable just like $\theta$. We can take this even a step further by meta-learning a learning rate for every individual inner loop parameter and every step $j$. This variant is referred to by the authors [45] as a per parameter per step learning rate type. We are effectively learning $k$ times as many learning rates as model parameters. We use the Hadamard product on line 13 to denote that the product between the learning rates in $\alpha$ and the gradient is performed componentwise. The subscript $j$ of $\alpha$ denotes that we have different learning rates in each step $j$.

After $k$ iterations of the inner loop, we recompute the loss for the inner loop parameters of the last step. On line 15 we perform a gradient update of the meta-learned model parameters and the learning rates $\alpha$. This is a gradient of gradients: backpropagation is applied to the computation graph of the inner loop that itself contains the inner loop gradient updates. We continue on line 8 by sampling the next image and repeat the process. After all outer loops have finished, we return the meta-learned weights $\theta$ and learning rates $\alpha$.

6.2. Overfitting from Meta-Learned Initializations

At the beginning of the overfitting phase, we make use of parameter-wise learning rates obtained from meta-learning. Basically, we just run the inner loop once which gets us already close to the final image in just $k = 3$ steps as shown in Algorithm 2. We then continue optimizing with Adam. The momentum terms of the Adam optimizer are uninitialized at this point. We have found that linearly increasing the learning rate in a warmup phase of 100 epochs prevents an initial degradation of reconstruction quality and even im-

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Algorithm 1 MetaSiren (modified version of MetaSDF [45] Algorithm 1)

1: **Required Inputs:**
2: $\mathcal{D}$: dataset for meta-learning
3: $\alpha_{init}$: initial learning rates for inner loop
4: **procedure** TRAININITIALIZATION($\mathcal{D}, \alpha_{init}$)
5: Randomly initialize $\theta$
6: $\alpha \leftarrow \alpha_{init}$
7: **for** $i \in [1, n]$ **do**
8: Sample training image $x^i \sim \mathcal{D}$
9: Get coordinates $p = \text{coord}(x^i) \in [-1, 1]^{W \times H}$
10: Initialize $\phi_0^i \leftarrow \theta$, $\mathcal{L} \leftarrow 0$
11: **for** $j \in [0, k - 1]$ **do**
12: $\mathcal{L} \leftarrow \text{MSE}(f_{\phi_j^i}(p), x^i)$
13: $\phi_{j+1}^i \leftarrow \phi_j^i - \alpha_j \odot \nabla_{\phi_j^i} \mathcal{L}$
14: $\mathcal{L} \leftarrow \text{MSE}(f_{\phi_0^i}(p), x^i)$
15: $\theta, \alpha \leftarrow (\theta, \alpha) - \beta \nabla_{(\theta, \alpha)} \mathcal{L}$
16: **return** $\theta, \alpha$

Algorithm 2 Overfit INR starting from a meta-learned initialization

1: **Required Inputs:**
2: $x$: the image to overfit
3: $p$: coordinate grid at desired resolution
4: $\theta_0$: meta-learned initialization
5: $\alpha$: meta-learned learning rates
6: **procedure** OVERFITMETA($x, p, \theta_0, \alpha$)
7: **for** $j \in [0, k - 1]$ **do**
8: $\theta_{j+1} \leftarrow \theta_j - \alpha_j \odot \nabla_{\theta_j} \text{MSE}(f_{\theta_j}(p), x)$
9: $\theta \leftarrow \theta_k$
10: $\theta^* \leftarrow \text{arg min}_\theta \mathcal{L}(x, f_\theta(p))$
11: **return** $\theta^*$

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1https://github.com/vsitzmann/metasdf
Figure 12. Comparing the meta-learned approach evaluated on Kodak with and without a warmup phase in the beginning of the training. We achieve better performance at higher bitrates when using a warmup phase.

Table 1. Default architecture hyperparameters.

| Description          | Value |
|----------------------|-------|
| Hidden layers $N$    | 3     |
| Activation function  | $\sin(30 \times x)$ |
| Input encoding       | Positional with $\sigma = 1.4$ |
| Input frequencies $L$| 16 (Kodak), 12 (CelebA) |

Table 2. Default hyperparameters for learning the initializations.

| Description                                    | Value |
|------------------------------------------------|-------|
| Outer loop initial learning rate $\beta$      | $5 \cdot 10^{-5}$ |
| Outer loop batch size                         | 1     |
| Outer loop optimizer                          | Adam [29] |
| Epochs                                        | 30 (DIV2K), 1 (CelebA) |
| Inner loop initial learning rate $\alpha_{init}$ | $10^{-3}$ |
| Learning rate type                            | per parameter per step |
| Inner loop steps $k$                          | 3     |
| Steps until validation                        | 500   |
| LR schedule patience                          | 10    |
| LR schedule factor                            | 0.5   |

Table 3. Default hyperparameters for overfitting the INR.

| Description          | Value |
|----------------------|-------|
| Initial learning rate| $5 \cdot 10^{-4}$ |
| Optimizer            | Adam [29] |
| Epochs               | 25000 |
| Steps until validation| 1     |
| LR schedule patience | 500   |
| LR schedule factor   | 0.5   |
| Early stopping epochs| 5000  |

Table 4. Default values for the quantization and bitstream coding related stages.

| Description                                    | Value |
|------------------------------------------------|-------|
| Initial learning rate                          | $5 \cdot 10^{-4}$ |
| Optimizer                                      | Adam [29] |
| Epochs                                         | 25000 |
| Steps until validation                         | 1     |
| LR schedule patience                           | 500   |
| LR schedule factor                             | 0.5   |
| Early stopping epochs                          | 5000  |

Met-Learning the Initializations. In Table 2 we list the default values of the hyperparameters for meta-learning the initializations. We use a learning rate schedule that halves the learning rate when no improvement has been made in the last 10 (= patience) validations. For validation we use a subset of 100 images sampled from the validation set of the respective dataset, in our case CelebA or DIV2K. We compute the validation loss by running the inner loop optimization for each image in the validation subset. The fact that computing the validation loss involves inner loop training is the reason why we limit the validation set size to 100. When we train the initializations on CelebA we train for 1 epoch. When using the DIV2K dataset we train for 30 epochs because it is a significantly smaller dataset. We finally, save the initialization that achieved the lowest validation loss overall.

Overfitting. The default hyperparameters for the overfitting stage are shown in Table 3. Since we are overfitting, we validate on the training image itself. We reduce the learning rate by a factor of 0.5 if the loss has not improved during the last 500 epochs. Note that 1 epoch equals 1 optimizer step, in other words, one training batch contains all pixels of the image we overfit. We train for 25000 epochs to make sure every architecture and configuration we test has the chance to reach convergence. As to be expected, smaller models typically reach peak performance faster. We stop training if the loss has not improved in the last 5000 epochs to prevent unnecessary computation resource use. In the end, we return the parameters of the model that has achieved the lowest loss during overfitting.

Quantization, Post-Quantization Optimization & Entropy Coding. In Table 4 we show the default values for the quantization and bitstream coding related stages. We emphasize that per default we use the combination of
Figure 13. Comparison of different quantization bitwidths for the meta-learned approach. The PSNR achieved by the unquantized models is shown by the dashed horizontal lines. Note that these are not rate-distortion curves and are only supposed to show the distortion introduced by quantization.

| Description                  | Value                  |
|------------------------------|------------------------|
| Bitwidth                     | 7 (Meta-Learned), 8 (Basic) |
| Retraining epochs            | 300                    |
| Optimizer                    | Adam [29]              |
| Retraining learning rate     | 10−6                   |
| AdaRound iterations          | 1000                   |
| AdaRound regularizer         | 10−4                   |
| Bitstream coding             | arithmetic coding      |

Table 4. Default hyperparameters for quantization, post-quantization optimization and bitstream coding.

AdaRound and QAT.

6.4. Influence of Quantization Bitwidth

We show the influence of bitwidth on the rate-distortion performance in Fig. 13 for the meta-learned approach and in Fig. 14 for the basic approach. For the meta-learned approach 7-bit is the best choice for both datasets. For the basic approach however, 8-bit quantization outperforms lower bitwidths. On the Kodak dataset the difference between 7- and 8-bit quantization is quite small nevertheless. We also show the unquantized performance of the 4 MLPs with varying number of hidden units as dashed horizontal lines. We see that for a bitwidth of 8 we can almost reach unquantized performance for the majority of configurations.

6.5. Generalization of Meta-Learned Initializations

We want to show that the meta-learned initializations are able to generalize to out-of-distribution images, even if the meta-learning dataset contains only similar images. To this end, we minimally crop and resize Kodak images to the same resolution and aspect ratio as CelebA (178 × 218) and then compress them using meta-learned initializations obtained from CelebA. In Fig. 15 we show that the meta-learned approach still outperforms the basic approach.

Figure 14. Comparison of different quantization bitwidths for the basic approach. The PSNR achieved by the unquantized models is shown by the dashed horizontal lines. Note that these are not rate-distortion curves and are only supposed to show the distortion introduced by quantization.

Figure 15. Generalization experiment: Using meta-learned initializations trained on CelebA evaluated on (cropped and resized) Kodak images. The meta-learned initializations provide enough generalization capability to improve compression performance also on out-of-distribution images.

6.6. Additional Image Examples

We show additional compression examples to compare our method to the codecs JPEG and JPEG2000. We first show more images at the lowest bitrate, i.e. using the lowest hidden dimension, where our method is most competitive to JPEG2000: In Fig. 16 we evaluate on KODAK using a model with $M = 32$ and in Fig. 17 we evaluate on CelebA using a model with $M = 24$. We visually confirm a clear advantage over JPEG for all images and similar performance as JPEG2000 at this bitrate. Moreover, we show examples at higher bitrates, i.e. using larger hidden dimensions, in Fig. 18 (Kodak) and Fig. 19 (CelebA). While our method maintains an advantage over JPEG, JPEG2000 outperforms our approach with an increasing advantage towards higher bitrates, where the difference is most apparent in the rendering of fine details.
Figure 16. Performance comparison on Kodak using a hidden dimension of $M = 32$ for all models.
Figure 17. Performance comparison on CelebA using a hidden dimension of $M = 24$ for all models.
Figure 18. Performance comparison on Kodak using a hidden dimensions of $M = 48$ (top), $M = 64$ (middle), $M = 128$ (bottom).
Figure 19. Performance comparison on CelebA using a hidden dimensions of $M = 32$ (top), $M = 48$ (middle), $M = 64$ (bottom).