Reducing Storage in Large-Scale Photo Sharing Services using Recompression

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Abstract—The popularity of photo sharing services has increased dramatically in recent years. Increases in users, quantity of photos, and quality/resolution of photos combined with the user expectation that photos are reliably stored indefinitely creates a growing burden on the storage backend of these services. We identify a new opportunity for storage savings with application-specific compression for photo sharing services: photo recompression.

We explore new photo storage management techniques that are fast so they do not adversely affect photo download latency, are complementary to existing distributed erasure coding techniques, can efficiently be converted to the standard JPEG user devices expect, and significantly increase compression. We implement our photo recompression techniques in two novel codecs, ROMP and L-ROMP. ROMP is a lossless JPEG recompression codec that compresses typical photos 15% over standard JPEG. L-ROMP is a lossy JPEG recompression codec that distorts photos in a perceptually un-noticeable way and typically achieves 28% compression over standard JPEG. We estimate the benefits of our approach on Facebook's photo stack and find that our approaches can reduce the photo storage by $0.3-0.9\times$ the logical size of the stored photos, and offer additional, collateral benefits to the photo caching stack, including 5-11% fewer requests to the backend storage, 15-31% reduction in wide-area bandwidth, and 16% reduction in external bandwidth.

Index Terms—JPEG, image compression, photo-sharing service, photo storage.

I. INTRODUCTION

In recent years, there has been a dramatic growth in the popularity of large-scale photo sharing services such as Facebook, Flickr, and Instagram. As of 2013, Facebook alone had 350 million photo uploads per day [1]. The storage footprint of these services is already significant; Facebook stored over 250 billion photos according to the same 2013 report [1]. Furthermore, the commoditization of high-quality digital cameras in mobile devices has created three trends that each increases the footprint of these services: people are taking more photos, at higher resolution, and at higher quality. These trends combined with the user expectation that photos are stored indefinitely results in an ever growing storage footprint.

Today, photos uploaded to photo sharing services predominantly use the JPEG [2] standard, which already compresses images by leveraging properties empirically observed in natural images. Despite this compression, as photo sharing

service scale, additional tools for managing photo storage become necessary.

One technique, already used in Facebook's f4 system [3], is distributed erasure coding. This reduces the storage footprint of a service by replacing the redundant copies of data that were used for fault tolerance and load balancing requests with combined parity information for multiple sets of data. Another prominent technique explored by the storage systems community is deduplication (Section V). To our knowledge, this has not been applied to images, in part because it is not clear if, after JPEG's compression, duplicate elimination is likely to provide significant benefit. For a similar reason, generic object compression techniques—e.g., gzip, bzip2—are unlikely to produce additional savings in storage.

Two other tools are available to large-scale photo sharing services: image resizing and reducing JPEG's quality parameter (this is a lossy transformation that re-quantizes information to enable better compression). As cameras and displays move towards higher resolution, users will likely want to view larger images, so the benefit of image resizing is limited. Moreover, as we show later, reducing JPEG's quality parameter by re-quantization can introduce significant error (uploaded images have already been quantized once when the JPEG was generated at the source).

In this paper, we focus on the problem of *image recom*pression: taking uploaded compressed images, and recompressing them by taking advantage of the special characteristics of large-scale photo sharing systems. Recompressing images reduces the logical size of the stored corpus and thus is complimentary to more generic techniques like distributed erasure coding.

There are three primary challenges for recompression schemes. The first is finding opportunities for additional compression given that images are already compressed. The second is to introduce minimal error if lossy recompression is used, a property that reducing JPEG's quality parameter does not have. The third stems from ensuring compatibility with client devices. Maintaining compatibility requires clients receive images in the JPEG format their devices understand and this in turn requires decompression from the storage format back into JPEG on the download path. This means that decompression should be fast (or, equivalently, have *low complexity*)—i.e., it should take <0.1s and ideally

<50ms—because it adds to the user-perceived download latency of a photo sharing service (Section II).

Contributions. Our key insight that enables this recompression is that large-scale photo sharing services represent a different domain than those for which image formats were designed. The large-scale aspect enables further compression of already compressed photos. At a high level, our approach decouples the size of the codec tables used for encoding and decoding many types of images. This decoupling enables much richer and larger codec tables than that are practical for individual files, i.e., the size of these large tables can be amortized over the large-scale storage and thus become negligible. In addition, in contrast to the traditional compression setting that considers individual images sent between a distinct sender and receiver, recompression for photo sharing services involves many photos that are compressed and decompressed by the same entity. These insights leads to our first recompression scheme, Recompression Of Many Photos (ROMP, Section III).

ROMP achieves high recompression rates by replacing the small coding tables that are stored with each image (or used by encoders/decoders as default) in traditional schemes with a single large coding table that is not stored with the images. The co-location of compression and decompression allows ROMP to avoid storing the coding table with each image. Instead, it stores the table in the memory of machines on the download path. This in turn allows ROMP to use a much larger coding table than would be practical for individual images. Such significant increase in coding table sizes can be amortized over the billions of photos for large-scale storage. ROMP achieves low complexity by keeping the coding table in memory on the download path of a photo sharing service and only making a single pass over an image.

ROMP provides high compression and low complexity for recompressing many photos and is lossless, i.e., recompressing a JPEG into ROMP and back produces a bit-wise identical image. For further compression gains, one could think of using other existing image compression algorithms (e.g., JPEG 2000 [4]). Note, however, that JPEG is the de facto standard for "raw" image representation, that is, most images are first stored as high quality JPEG files on a digital camera. Then, applying other compression schemes would require decoding JPEG images (at upload) and generating again JPEG images (at download), as many potential clients only support JPEG, which would incur a significant complexity penalty. As a result, the standard method for recompressing images is decreasing JPEG's quality factor, but this increases distortion due to doublerounding of image coefficients. Our Lossy-Recompression Of Many Photos (L-ROMP) is designed to reduce bit-rate in JPEG images and avoids this double-rounding problem. L-ROMP amplifies the compression gain of ROMP, adds no addition complexity to decompression, and is perceptually nearly lossless. ROMP and L-ROMP have been published in [5]. This paper includes more results for evaluation of ROMP and L-ROMP. More importantly, this paper focuses more on leveraging ROMP and L-ROMP in photo sharing services, but not the codec itself, and presents system level evaluation.

In addition to a storage backend, photo sharing services typically deploy a photo-caching stack [6]. The stack is a set of caching layers that are progressively smaller and closer to clients. The goals of the stack are three-fold: to reduce the load on the storage backend, to reduce the amount of external bandwidth needed to deliver photos, and to decrease user-perceived download latency. The most straightforward deployment of ROMP would place the decompression step between the storage backend and the caching stack. We find, however, that doing the decompression inside the caching stack would improve each of the three goals. We term these "collateral benefits" because they are in addition to the reduction in storage cost.

Our evaluation explores the compression and complexity of ROMP and L-ROMP across a variety of image qualities and resolutions. We find that ROMP and L-ROMP robustly provide high compression—approximately 15% and 28% over JPEG Standard respectively-and low complexityless than 60ms decompress time. This translates to 13% and 26% compression over JPEG Optimized². These storage savings multiply when integrated into the photo-sharing services. Because photos are replicated or erasure coded in the backend for fault-tolerance, ROMP and L-ROMP can reduce the storage footprint by $0.5\times-0.9\times$ the logical size of stored photos using the lossless/lossy codecs respectively. We also estimate the collateral benefits of deploying our schemes in Facebook's photo caching stack. These would, for example, include 5%-11% fewer requests to the backend storage, a 15%-31% reduction in wide-area network bandwidth, and a 500ms decrease in 99th percentile photo download latency.

II. INTEGRATING RECOMPRESSION INTO PHOTO SHARING SERVICES

In this section, we discuss the benefits, for large-scale photo sharing services, of recompressing uploaded images and how to integrate the functionality provided by ROMP or L-ROMP into these photo sharing services. Our discussion is especially informed by the descriptions of Facebook's photo sharing stack [7], [3], [6], and our measurements of it.

From a systems point of view, ROMP and L-ROMP each consist of two conceptual modules: a compression module

¹[5] presents the compression ratio results of Figures 7a and 7b (but not complexity results), and complexity results of Figure 9a for quality parameter 75 only. These are the only overlap in results presented in the two papers

²JPEG Optimized is a lossless compression technique for JPEG Standard format, which provides additional compression with negligible overhead. It is a more popular JPEG format.



Fig. 1: A typical upload path (1–6) for a large-scale photo sharing service. Photos are sent synchronously from users to backend storage via front-end Web servers and a transcoding tier.

that recompresses an uploaded image, and a decompression module that decompresses images before download.

Compressing on Upload. A typical upload path for a large-scale photo sharing service is shown in Figure 1. Users upload photos to the service synchronously, i.e., the user waits until the photo is safely stored in the backend storage. The user's device initially sends the photo to a front-end Web server that handles incoming requests from clients (1). That Web server then sends the photo to a transcoder machine in the transcoding tier (2). The transcoder then sends the photo to the backend storage tier (3), and, once the photo is safely stored, acknowledgements flow in the reverse direction (4–6).

The transcoder sits on the upload path and canonicalizes photos before storing them. This canonicalization typically involves resizing photos and/or reducing the JPEG image quality. The JPEG standard permits the reduction of image quality using a scalar *quality parameter*. This quality reduction reduces the storage required for images but can introduce undesirable perceptual artifacts. Resizing photos gives them standard sizes and ensures that photo storage growth is consistent and predictable. For instance, this prevents the release of a new popular phone model with a higher resolution camera from increasing the required storage per photo. Reducing image quality to a fixed factor also keeps storage growth consistent and predictable for similar reasons. Both of these transformations are *lossy*, a topic we cover and explore in more depth in Section III.

Given that the transcoding tier is already doing image processing on uploaded photos it is a natural place to also do recompression. Doing recompression here requires that compression must have low *complexity* (time taken to recompress the images). In particular, the complexity of recompression must be comparable to, or less than, the complexity of resizing or reducing image quality.

An alternative place to integrate recompression of photos would be off the upload path. This would require storing the photos in their initial format and then recompressing them during off-peak periods. This might be feasible but adds complexity to the entire path: these recompression operations may need to be carefully scheduled, and the download path (described below) needs to be able to retrieve images before they have been scheduled for recompression (since users expect images to be available immediately). For these reasons, we do not consider this alternative in this

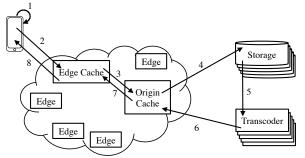


Fig. 2: A typical download path (1, 1-2-8, 1-2-3-7-8, or 1-8) for a large-scale photo sharing service. A photo is returned from the first cache in the path that has it. If the photo is not present in any of the caches it is fetched from the backend storage via the transcoding tier (4-6).

paper.

Decompressing on Download. A typical download path for a large-scale photo sharing service in shown in Figure 1. Users download photos from the first on-path cache they encounter with the photo: the device cache (1), the edge cache that handles their request (1-2-8), or the origin cache (1-2-3-7-8). If the photo is not in one of those caches it is fetched from the backend storage system via a transcoder (1–8).

The transcoder converts the photo from the format and size as stored in the backend to what will be delivered to a user device. For instance, Facebook transcodes stored JPEGs into the WebP format before sending them back to Android devices [8]. The transcoder tier also resizes photos depending on their destination [6]. For instance, a desktop user with a large open window may receive a larger version of the photo than a different desktop user with a smaller open window.

The transcoding tier is again a natural place to do decompression on the download path because it is already manipulating photos. This placement of decompression on the download path leads to a requirement that it have low complexity, to ensure both low latency for user requests for photos and a small impact on the required size of the transcoding tier.

Complexity/Storage Tradeoff. ROMP trades-off additional complexity for greater savings in storage. The storage saving is of more important because that the storage increases linearly with time, but the additional complexity does not: recent measurements of photo sharing services suggest that each image is viewed many times soon after they are uploaded, and very rarely thereafter [3]. This means that the complexity cost is never proportional to time.

Benefits of Low Complexity Decompression. Even though the storage saving is more significant over time, it is still important to have low complexity, especially for decompression. The reason is that *low complexity in the download path ensures low access latency*. Large-scale content delivery services optimize latency aggressively and moderate increases in latency can negatively impact user experience.

The latency introduced by decompression may not affect all downloads, because of caching. For example, if an image is decompressed and transcoded once, it can be cached either at the origin cache or the edge cache for subsequent accesses (unless the subsequent accesses are from devices of a different type or a different resolution, in which case decompression must happen again). However, even if only cache misses require decompression (about 29% [6]), it is still important to have a low latency decompression.

The most well-known efficient JPEG recompression scheme, PackJPG [9], can provide about 20% additional compression in photo sizes, but has significant decompression complexity.³ For downloading a 2048×1536 image from the backend, PackJPG's recompression inflates the latency of the fastest 40% of downloads by more than 50%. Even though the decompression latency is incurred only for cache misses, we still see significant impact on the overall latency distribution (from all the layers of the cache stack): ~80% of the distribution incurs more than 150ms additional latency.⁴ For commercial photo sharing services, these increases in latency may not be acceptable.

These photo services can also reap other benefits of recompression. For example, moving the decompression and transcoding close to the clients can have two important benefits. First, caches would now be more storage efficient, because they would store recompressed versions of the photos. This would result in fewer accesses to the backend storage and caches. Second, the bandwidth required between the caches and the backend storage would be reduced because only recompressed images would need to be transferred. However, to reap these benefits, the additional decompression latency would affect *all the accesses*. In this case, low complexity decompression is even more important, using the state-of-the-art PackJPG, with its high decompression complexity, can increase latency by more than *half a second*.

For this reason, we make low complexity decompression a primary design requirement for ROMP and L-ROMP.

III. LOW-COMPLEXITY RECOMPRESSION FOR PHOTO SHARING SERVICES

In this section, we discuss the need for a new recompression strategy, and then describe the design of ROMP and L-ROMP, which recompress JPEG images to reduce the storage requirements of large-scale photo sharing services significantly with low complexity overhead.

A. Why a New Recompression Strategy?

Limitations of Traditional Approaches. While photo storage services such as Flickr maintain a copy of the original uploaded images, large-scale photo sharing services modify the uploaded image in order to manage the scale of their storage infrastructure. Specifically, Facebook (a) resizes images and (b) recompresses them using a smaller quality parameter.

Resizing, while useful in managing storage, has its limits. Camera resolution has been increasingly steadily over the last five years, as have display resolutions, even on mobile devices. As a result, it is likely that photo sharing services will increasingly face pressure to serve high-resolution images in the near future, so photo sharing services will need additional tools to manage photo storage.

Recompressing an image by reducing JPEG's quality parameter (requantizing) is a convenient knob for managing storage; for example, most cameras generate high-quality images at quality parameter of 95, but Facebook reduces the quality parameter on an uploaded image to ~75. To achieve further storage saving, we have to apply the second quality parameter reduction. As we demonstrate experimentally in Section IV, two consecutive quality parameter reductions lead to unacceptable quality degradation.

In summary, while resizing and quality adjustments are currently used, they are not a viable solution for producing additional storage savings. Thus, in this paper we explore a completely different approach for recompression, enabled by the unique setting of photo-sharing services.

New Opportunities in Photo-Sharing Services. As opposed to traditional sender/receiver compression scheme where sender encodes the image and the receiver decodes it, the large-scale photo sharing services represent a new compression setting, with some special properties that offer opportunities for better compression.⁵

Property 1: Collocated Encoder/Decoder. Instead of having two distinct sender/receiver entities where the encoder and the decoder are in physically separate locations, the recompression setting in photo-sharing service includes both compression and decompression within the service. In traditional distinct encoder/decoder setting data is typically encoded in one of two ways. One is using a default codec (e.g., JPEG Standard) that is present at the sender and receiver of the data and does not need to be transmitted with it. The other is using a customized codec table (e.g., JPEG Optimized) that is customized at the sender, transmitted along with the data to the receiver, and then used to decode the data. A customized codec table can typically represent the data more compactly than a default table, but there is a tension between the size of the codec table and the compactness of its representations. Larger customized codec tables often

³A more recent recompression scheme, Lepton [10], does achieve lower latency than PackJPG. We will evaluate Lepton in Section IV.

⁴The methodology for this experiment is explained in Section IV-D.

⁵We use encode/decode and compress/decompress interchangeably.

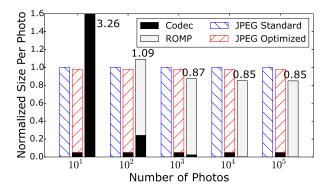


Fig. 3: Normalized storage size per photo of codec + image using JPEG Standard, JPEG Optimized, and ROMP for an increasing quantity of 2048×1536 photos. ROMP makes sense at the large scale it was designed for where the size of its larger codec is negligible compared to the storage saving it offers.

lead to higher compression because they can model the data more effectively. Yet, the customized codec table must be kept small to ensure that the space savings obtained by the richer encoding is not negated by having to transmit the table along with the data.

In the collocated setting the encoder and decoder are at the same location and thus the codec table used for encoding the data can be decoupled from the data itself. This decoupling removes the constraint on the size of codec tables: the codec tables can be much larger than what is practical for individual files because they are shared across many files and stored separately. As a result, this new design can potentially reduce the storage of a service beyond what standard approaches can achieve.

Property 2: Large-Scale Photo Storage. Despite the freedom to use large codec tables, the codec table constitutes storage overhead that must be carefully managed. However, the large-scale aspect of photo-sharing services helps in this regard: the same codec overhead that would negate the additional storage reduction in a small-scale case will become negligible for large-scale case as it will be amortized across the entire storage (Figure 3) because the codec tables are shared across many photos. At small scales, this large codec tables (Section III-B) can be much larger than the image itself. In contrast, at large scale, the size of the ROMP codec is negligible compared to the size of the stored images, e.g., in ROMP design, it needs to store 10,000 images to make the codec negligible. Our evaluation in Section IV shows that these larger shared tables can compress photos better than traditional customized tables, and have other benefits across the photo stack.

In summary, enabled by the collocating of encoder/decoder and the large-scale setting, large codec tables can be used which would not be practical for traditional

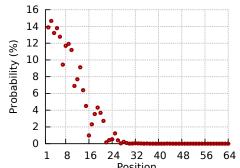


Fig. 4: Probabilities of 3 Bit Coefficients at different positions

small-scale sender/receiver setting. In the following two subsections we describe: (a) ROMP, a lossless coding technique that uses enhanced Huffman tables, and (b) L-ROMP, a perceptually near-lossless coder that does not suffer from the significant quality degradation inherent in re-quantization. At a high level, ROMP and L-ROMP make use of a large set of codec tables generated from a large corpus of images, where each of the tables is optimized for a specific context, and has similar structure as that of a typical JPEG entropy coding table. Other than using the new codec tables, ROMP and L-ROMP proceed block by block and does not involve any transformations or re-orderings of DCT coefficients. This ensures that the coding complexity is very low (see Fig. 5), which is approximately equivalent to a JPEG entropy decoding followed by a JPEG entropy coding. Together, these techniques can reduce photo storage requirements by 25% or more, a significant gain for large photo sharing services that store billions of images.

B. ROMP: Lossless Coding using Enhanced Huffman Tables

Our design, ROMP, exploits the decreasing cost of storing and managing large tables by designing *context-sensitive* coding tables that result in lossless compression. Recall that JPEG's Huffman tables are used to code symbols (information about run-lengths and quantized values), based on the expected frequency of symbols' occurrence. ROMP learns context-sensitive Huffman tables by learning the empirical probability of occurrence of these symbols from a large corpus of images. This learning leverages the availability of such corpora in a large-scale photo service. Concretely, ROMP uses below two insights derived from properties of natural images to obtain context-sensitive Huffman tables.

Position-dependence. The empirical probability of occurrence of a symbol can depend on its position in the zig-zag scan. That is, for a given symbol, its empirical probability of occurrence at position p_a along the zig-zag scan is likely to be different from its empirical distribution at position p_b (Figure 4 illustrates this). For example, for natural images, it is known that non-zero coefficients are increasingly unlikely at higher frequencies [11]. Thus, if $p_b > p_a$ then a non-

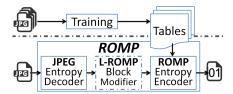


Fig. 5: ROMP Encoding Architecture

zero value will be less likely at p_b . For this reason, ROMP generates different tables for different positions: i.e., position is one aspect of the context used for encoding. Thus, the same symbol may be encoded using different bit-patterns depending on the position where it occurs.

Energy-dependence. The second insight is based on the observation that, relative to image sizes predominantly in use today, an 8×8 block represents a very small patch of the image. To see this, imagine capturing the same visual information (a photo of a person, say) with two cameras of different resolutions, and then using JPEG encoding for both images. Clearly 8×8 blocks in the higher resolution image represent smaller regions of the field of view, and thus will tend to be smoother. This has two useful implications. First, information within a block will tend to be smooth, with additional smoothness expected for larger images. Smoother images are such that coefficients at higher frequencies tend to be smaller. Second, because the same region in the field of view comprises more blocks when larger images (higher resolutions) are generated, it becomes more likely that neighboring blocks will have similar characteristics.

We exploit these two ideas by creating tables such that the probability of occurrence of a symbol at a given position can also depend upon the *energy* of other coefficients within the block (*intra-block* energy) and of neighboring blocks (*inter-block* energy). For a given *runsize* that occurs at zigzag position p of the n-th block, we use the average of the observed coefficient sizes in a block as an estimate of intra-block energy:

$$intra(n,p) = \frac{1}{p-1} \sum_{i=1}^{p-1} \frac{SIZE(b_n(i))}{max_{SIZE}(i)}$$
 (1)

where b_n denotes the n-th block, and $b_n(i)$ denotes the coefficient at position i, $SIZE(\cdot)$ denotes the bits required to represent the amplitude of the coefficient, $max_{SIZE}(i)$ is the observed maximum coefficient size for position i of images in the training set.

Similarly, the inter-block energy value is estimated based on the average sizes of coefficients in nearby blocks: F nearby zigzag positions in B adjacent prior blocks (ROMP uses F = 5 and B = 3):

uses
$$F = 5$$
 and $B = 3$):
$$inter(n, p) = \frac{1}{B \cdot F} \sum_{i=n-B}^{n-1} \sum_{j=p}^{p+F-1} \frac{SIZE(b_i(j))}{max_{SIZE}(j)}$$
(2)

Putting it all together. Context in ROMP is defined by a triple $\langle p, i, e \rangle$ to define context: zigzag position p,

intra-block energy *i* and inter-block energy *e*. Note that the statistical dependencies captured by this context information are well known in image coding and exploited by state of the art compression techniques, but to the best of our knowledge we are the first to take advantage of them for low latency JPEG transcoding (where complexity is minimized by using memory to store many, context-dependent Huffman tables).

At a high-level, ROMP works as follows (Figure 5). From a training set of images, ROMP learns a Huffman table for each unique context (i.e., for each unique combination of position, intra- and inter-block energy). For runsize that occurs in any image in the training set, ROMP first determines its context triple and then gathers it together with other runsizes belonging to the same context. After gathering all the runsizes for each context, ROMP can generate a table for this context based on the number of occurrences of each. ROMP pre-defines 20 different energy levels for both intra-energy and inter-energy, which leads to $\sim 64 \times 20 \times 20 = 25600$ different contexts and Huffman tables to be learned.⁶ These tables are quite different, which allows ROMP to achieve better compression over standard JPEG. When an image is uploaded, ROMP decodes the JPEG image, computes the corresponding triple $\langle p, i, e \rangle$, the then uses the learned Huffman tables to re-code the image. Before delivering an image to a client, ROMP reverses its context-sensitive entropy code, then applies the default JPEG entropy code.

C. L-ROMP: A Gracefully Lossy Coder

ROMP's entropy coder is lossless with respect to the uploaded JPEG. In this section, we describe L-ROMP, which introduces a controlled, perceptually insignificant, amount of loss (or *distortion*) in uploaded images, as a way of achieving further savings in photo storage.

As discussed previously, users upload high quality JPEG images and many photo sharing services, e.g., Facebook, change the JPEG quality parameter to a lower level in order to ensure predictable storage usage, a step that introduces additional distortion. Figure 6 quantifies the dramatic increase in distortion caused by re-quantization, compared to quantizing the original raw image directly to the target quality parameter, showing rate-distortion performance with two different objective quality metrics: PSNR and MS-SSIM. The "Re-quantize (raw)" curve is obtained by reducing the quality parameter when compressing the original raw images, while the "Re-quantize (JPEG)" curve is obtained by re-quantizing a high-quality JPEG image derived from the same set of raw images. The former curve represents much more graceful degradation. By contrast, re-quantization introduces much more distortion for the same size reduction. This happens because the latter suffers from cumulative errors due to two consecutive re-quantizations.

⁶These tables take up less than 16MBs of the memory, a negligible memory usage increment for modern machines.

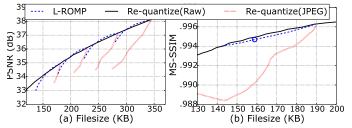


Fig. 6: Rate/distortion performance of L-ROMP, compared to re-quantization from raw image and from JPEG image using Tecnick images of 1200×1200. (a): Using PSNR as the quality metric, and showing performance on JPEG images of four quality parameters (70,80,86,90). (b): Using MS-SSIM metric, and focusing on JPEG images of quality parameter of 75; "o" marks the perceptually lossless setting of L-ROMP.

L-ROMP avoids re-quantizing coefficients, but introduces distortion by carefully setting some non-zero (quantized) coefficients to zero, a specific instance of a general idea called thresholding [12]. The intuition behind thresholding is that, by setting a well-chosen non-zero coefficient to zero, it is possible to increase the number of consecutive zerovalued coefficients in the sequence of coefficients along the zig-zag scan. This in general helps reduce size as it replaces two separate runs of zeros together and a non-zero coefficient value, by a single run of zeros. Optimization of coefficient thresholding has been considered from a ratedistortion perspective in the literature [13], [12], we are not aware of it being explored as an alternative to re-quantization in large photo sharing services. Here we use a simplified version where only coefficients of size equal to 1 (i.e., 1 or -1) can be removed. This means that the distortion increase for any coefficient being removed will be the same.⁷ Thus, we only need to decide if for a given coefficient the bit-rate savings are sufficient to remove it. We make the decision by introducing a rate threshold and only thresholding a coefficient if the bits saving by doing so would exceed this threshold.

However, setting too many coefficients to zero within a block can introduce local artifacts (e.g., blocking). Thus, L-ROMP uses a *perceptual threshold* T_p that limits the percentage of non-zero coefficients that will be set to zero. By doing this L-ROMP can guarantee that the block-wise SSIM with respect to the original JPEG is always higher than $1 - \frac{T_p}{2-T_p}$. For example, if we use $T_p = 0.1$ (i.e., we can threshold at most 10% of the non-zero coefficients), then block-wise SSIM metric is guaranteed to be higher than 0.947. The proof of such bound is based on results from [14]

and is omitted for brevity.

In Figure 6 (a), we observe that L-ROMP degrades PSNR more gracefully than simply re-quantizing. We see that with conservative thresholds, L-ROMP's curve is actually higher than re-quantizing from the raw image curve, illustrating the efficiency of L-ROMP's trading distortion for bits-saving. L-ROMP performs equally well on MS-SSIM metric (plot (b)). To achieve perceptually lossless compression, we also conducted a subjective evaluation, by developing a comparison tool that can choose thresholds and shows the image at the chosen setting as well as size reduction. We find that using rate threshold of 2.0 and perceptual threshold of 0.4 provides maximum bits-saving without noticeable quality distortion ("o" of Figure 6 (b)). We use these parameters for L-ROMP.

Finally, L-ROMP can be easily introduced into ROMP's pipeline: before applying the context-sensitive entropy coding, L-ROMP's thresholding can be applied to each block (Figure 5). No changes are required to ROMP's entropy coder.

D. Encoding/Decoding in Parallel to Reduce Latency

A recompression codec that can achieve both high compression and low coding latency is ideal to photo sharing services. However, generally speaking, a high compression ratio codec introduces higher complexity, and thus higher coding latency at the same time. With reducing "complexity", a parallelized codec can reduce the coding latency, and some codecs have explored this idea [10]. Parallelizing can reduce the latency in terms of time, but because the codec still requires the same number of CPU cycles, it cannot improve the coding throughput. It means that, when CPU resources is the bottleneck, parallelized codecs would not have benefits. Because of this, the number of CPU cycles is the right metric for complexity.

However, when CPU resources is not the bottleneck, the capability of enabling parallelism is an important feature for recompression codecs to further reduce coding latency. ROMP can be easily extended to parallelized, multithreaded version. ROMP just needs to break the original image into N sub-images to enable ROMP's encoding in N threads. ROMP needs to save each encoded sub-image separately, with this sub-image's offset of the original JPEG image, i.e., for the original JPEG, where is the first bit of this sub-image. At the decoding, ROMP can enable N decoding threads, each decodes one encoded/compressed sub-image, but writes the decoded bits to the right location indicated by the offset information. By doing so, these N decoding threads collectively recover the original JPEG image.

Enabling N threads can take the encoding/decoding latency to approximately 1/N of the original, single-thread

⁷Note that the actual MSE will be different if two coefficients have same value 1, but different frequency weights in the quantization matrix. However, by ignoring this difference we take into account the different perceptual weighting given to each frequency and obtain better perceptual quality.

 $^{^8\}mbox{Actually, parallelized codec}$ will introduce additional CPU overhead to enable parallelism.

ROMP. The next question is whether the enabling of parallelism negatively affects compression. Multi-threaded ROMP requires more bits to represent the original JPEG, for two reasons. The first reason is that, multi-threaded ROMP needs to store the extra offset information. The second reason is that, to encode one block, ROMP uses B adjacent prior blocks to predict current block (inter-block energydependence). But for the first B blocks of each image, this information is not complete. This affects the predictability, and then the compressibility. Fortunately, these two penalties are both negligible for ROMP's compression. Offset information requires 64 bits per thread for an image that is no larger than 4GB. This is clearly negligible, as each thread usually handles hundreds of KBs data, a less than 0.01% penalty. The second penalty is also insignificant. Each thread will encode thousands of blocks (e.g., a 2048×1536 image contains 50000 blocks), only 3 (ROMP uses B = 53) of them are lack of information for prediction is not a big deal. On the other hand, for L-ROMP, enabling parallelism would not introduce any penalties. In our experiment, a 4thread ROMP reduces the coding latency to less than 1/3 of the original single-thread ROMP's latency, while only introduces 0.01% of extra bits. We conclude that ROMP and L-ROMP can both be extended to multi-threaded version easily.

IV. EVALUATION

We experimentally explore three key questions:

- How do ROMP and L-ROMP compare to the state of the art in terms of compression ratio and complexity under a variety of settings?
- What compression can ROMP and L-ROMP achieve and what storage savings does that translate into?
- What collateral benefits does ROMP and L-ROMP enable?

A. Methodology

- a) Implementation: Our evaluations use an implementation of ROMP that has two software components: a training script and a codec. The training script is implemented in Python and takes a training set of JPEG images, decodes them, and generates Huffman tables. Training is done once and is off-path for photo uploads and downloads and so it is not included in complexity measurements. The codec is implemented on top of libjpeg-turbo [15]. The implementation of L-ROMP is an extension of ROMP that adds an additional block-modification stage to the image processing pipeline. ROMP and L-ROMP are publicly available [16].
- b) Baselines: To quantify the compression ratios and complexity of ROMP and L-ROMP, we compare them with lossless JPEG codecs and alternative photo formats. The lossless JPEG codecs include all that we are aware of

that have publicly available implementations: JPEG Standard, JPEG Optimized, JPEG Progressive, JPEG Arithmetic, MozJPEG [17], PackJPG [9] and Lepton [10]. The alternative photo formats include WebP and JPEG2000.

- c) Image Sets: Our evaluation uses two sets of images:
- Tecnick [18] is an image set of 100 images, each available in many resolutions up to 1200 × 1200. The images are in a raw format (PNG), which allows us to transcode them to JPEGs of different resolutions and different quality parameters. We use Tecnick because it is commonly used in image processing benchmarks.
- FiveK [19] is an image set from MIT-Adobe that contains 5,000 publicly available raw images taken from different SLR cameras. This data set is used to evaluate images with higher resolution than the max of 1200×1200 in the Tecnick image set.
- d) Metrics: We evaluate our compression schemes and their baselines on two metrics: compression ratio, and encoding/decoding time. Compression ratio measures the storage efficiency and is the ratio of saved storage over old storage. More precisely, let s' be the size of an image generated by a scheme and s be the size generated by JPEG Standard. Then, the compression ratio is $\frac{s-s'}{s}$. The encoding time is the time to recompress from JPEG Standard and the decoding time is the time to decompress back to JPEG Standard. To make fair coding complexity comparison among schemes, we measure the encoding/decoding time of single-thread version of each scheme.
- e) Testing: The images used for our experiments are obtained from the image sets described above. For the small Tecnick image set, we use 10-fold cross validation: the 100 image set is divided into 10 groups of 10 images; we test on one group of 10 images after training on the other 90 images, and repeat this procedure for every group in order to test on every image of the set. For the FiveK image sets we use 1000 randomly chosen images for training and the rest of the images for testing.

B. Compression & Complexity

ROMP and L-ROMP are designed to provide high compression ratios with low complexity. This subsection compares the complexity and compression ratios of ROMP and L-ROMP against the state of the art. We evaluate under a variety of settings with an eye to the future where photos will be larger in size and higher in resolution.

a) Compression/Complexity Tradeoff: Compression techniques represent different points in the complexity vs. compression tradeoff. In general, with higher complexity—i.e., higher encoding/decoding time—higher compression ratio are possible. Figures 7a and 7b present this tradeoff for the alternatives considered in the paper, for

⁹The only scheme that supports parrellelism is Lepton [10], we use its single-thread version for evaluation.

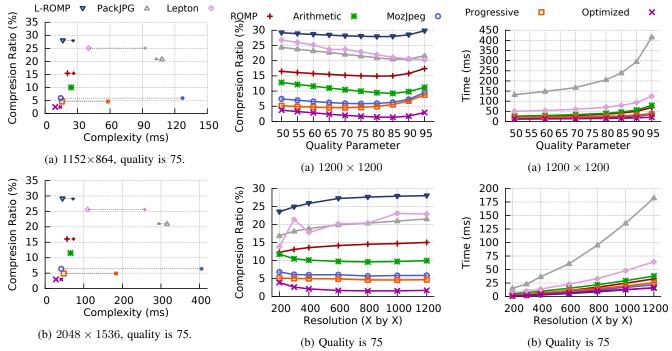


Fig. 7: Compression/complexity tradeoff the smaller shows the encoding complexity.

Fig. 8: The compression ratio over JPEG Fig. 9: The decoding complexity as (a) of FiveK image set. The bigger marker Standard baseline as (a) quality parameter quality parameter changes and (b) resochanges and (b) resolution changes for lution changes for Tecnick image set. (Y-Tecnick image set. axis ranges differ for readability.)

two different image resolutions and a quality parameter of 75 on the FiveK dataset. We exclude results for transcoding back and forth from other image formats, i.e., WebP and JPEG2000, because they are clear outliers: they require 700– 2900ms to decompress a 2048×1536 photo.

For encoding time, ROMP is comparable to JPEG Arithmetic, and much faster than other competitors. In particular, the high compression schemes, PackJPG and Lepton, both require roughly 4× encoding time. Compared to ROMP, L-ROMP's additional step of thresholding does not induce any extra complexity. Decoding time is the more relevant metric for ROMP because it affects user-perceived delay. ROMP's decoder is slightly faster than JPEG Arithmetic, comparable to JPEG Progressive and MozJPEG, 5× faster than PackJPG and 2× faster than Lepton. L-ROMP's decoder is identical to ROMP, but after thresholding the image becomes smaller, which makes it ~20% faster than ROMP. Interestingly, Pack-JPG is the only scheme whose decoding time is higher than its encoding time. Finally, ROMP has higher compression ratio than almost any other alternative: only PackJPG and Lepton achieve higher compression ratio.

This experiment shows that ROMP and L-ROMP occupy a unique position in the tradeoff space, achieving both high compression ratio (15 - 29%) and low complexity (60ms encoding/decoding time for a 2048×1536 image). By contrast, the other high-compression schemes, PackJPG and Lepton, have a compression ratio of 20%, but this comes at considerable complexity cost. Their encoding time are over 250ms, and decoding time are over 110ms (more precisely, PackJPG's decoding is more than 310ms), which we consider unacceptable because it would shift the latency distribution significantly (Figure 12).

b) Compression Ratio as Quality and Resolution Increase: As camera technology continues to improve, we expect users to upload images with higher quality and resolution and thus the compression performance for higher quality parameters and resolutions is important. Figure 8a evaluates the compression ratio of ROMP, L-ROMP, and baselines as a function of varying quality parameter on the Tecnick dataset. These schemes are generally robust to changing quality factors, but with their lowest compression ratio around quality parameter 75. We believe this is because we are comparing against JPEG Standard and its Huffman tables are optimized for the widely used quality parameter, 75. The robustness of ROMP's compression is validated by this experiment, where we see compression ratios over 15% for all quality parameters.

Figure 8b explores the effect of the trend towards higher

resolution images. The figure shows the compression ratio of ROMP and L-ROMP over JPEG Standard for increasing image resolutions. ROMP's compression ratio increases with image resolution, in contrast with all other low complexity alternatives. ROMP's compression ratio is close to PackJPG and Lepton at the highest quality parameter. This is an important property given the trend towards larger image sizes with higher quality parameters. One reason for this good property is that ROMP can train and use different coding tables for different image parameters, while other schemes might have poor performances on certain image parameters. We have also verified this trend in the FiveK dataset (omitted for brevity).

c) Decoding Complexity as Quality and Resolution Increase: Figure 9a shows how decoding time scales with increasing quality of images. We observe that schemes with low decoding complexity scale well; the decoding time for PackJPG and Lepton, however, scales poorly with image size and image quality. Figure 9b shows how decoding time scales with increasing resolution of images. We see a similar trend to increasing quality; low decoding complexity schemes scale well. This re-affirms our findings that ROMP and L-ROMP are better codecs. ROMP occupies a sweet-spot in the complexity/compression tradeoff space: even though PackJPG and Lepton have higher compression ratio, it scales poorly with the trend towards larger, higher quality images. L-ROMP is an even better choice if perceptually indistinguishable changes are acceptable.

C. Storage Reduction for Photo Backends

This section estimates the compression ratios ROMP and L-ROMP can achieve for a real photo-sharing service, i.e., Facebook's photo storage system.

Above experiment demonstrates compression ratio over JPEG Standard, we need to translate above compression result to benefits over JPEG Optimize, which is more popular as it is a clear winner over JPEG Standard. We estimate ROMP and L-ROMP would result in 13% and 26% compression ratios respectively on JPEG Optimize (instead of 15% and 28% on JPEG Standard). This estimate is done by pre-optimize images we use in above experiment to JPEG Optimize and re-run the experiment. Note that, we see slightly different compression ratios on images with different quality parameter or resolution in above experiment, we download Facebook photos, get the average JPEG quality parameter and resolution and use that to pick these compression ratio values. These are the values we use later to calculate the storage reduction and collateral benefits of deploying ROMP and L-ROMP into the photo-sharing service.

a) Storage Reduction: The storage reduction from a compression scheme is greater than simply its compression ratio because photo sharing services replicate images for fault tolerance and load balancing. This results in a physical

		ROMP	L-ROMP
Compression	0%	13%	26%
Haystack	3.6×	3.1×	2.7×
f4	$2.1 \times$	$1.8 \times$	1.6×

Fig. 10: New effective replication factor if compression schemes were deployed based on the compression ratio over JPEG Optimized for large photos.

image storage that is a multiple of the logical size of the stored images, *i.e.*, the effective replication factor. Facebook's Haystack [7] has an effective replication factor of $3.6 \times$ and f4 [3] has an effective replication factor of $2.1 \times$.

Figure 10 shows how ROMP and L-ROMP would reduce the effective replication factor of Haystack and f4. The difference between the current effective replication factor and the new factor is the storage reduction due to the deployment of ROMP and L-ROMP. For instance, if ROMP was deployed on Haystack it would reduce the storage footprint by $.5\times$ the logical size of the images it stores, and if L-ROMP was used on Haystack, it would reduce the storage requirements almost by the size of one complete copy of the images $(.9\times)$. Similarly, if L-ROMP was used on f4 it would reduce the storage footprint by $.5\times$ the logical size of the images.

D. Collateral Benefits

This subsection quantifies, using a data-driven model-based approach, the collateral benefits of placing the decoder in the edge cache. These collateral benefits include a larger effective cache size, increased hit rates at the caches, reductions in backfill requests and bytes, and a reduction in external bandwidth when L-ROMP is used. L-ROMP can impact download latency, which we also quantify.

a) Methodology: Data-Driven Model-Based Estimation: We use a data-driven model-based approach to estimate the collateral benefits with the deployment of ROMP, on the photo stack of a large provider described in Figure 2. At a high level, each box in this figure is associated with a distribution of processing latencies, and each link with a distribution of transfer latencies. In addition, caches have an associated hit rate and we model cache hits by assuming that photos have uniform probability of a cache hit, given by the hit rate.

We combine multiple measurement results of the current photo stack to parameterize the model. We use measurements from a 2013 Facebook study [6] to get the cache hit rates for the model and we combine latency measurements from [6] and our recent measurement study [20] to obtain the transfer latencies for the model. We need to update the model in two ways: first, the processing latency due to decompression of ROMP or L-ROMP will need to be added

to the edge caches; second, the cache hit rates need to be recomputed, resulting in changes in the percentage of requests served by each cache layers and the distribution of download latency. We discuss these changes in the paragraphs below.

Cache Hit Rates. In the absence of ROMP, we assume the cache hit rates of edge caches and origin caches are based on measurement results from [6]. ROMP or L-ROMP would reduce the size of each image stored in a cache, which would allow each cache to store more images. To compute this effective cache size increase as a result of compression, we use the following model: for a codec with a compression ratio of x%, the cache size effectively increases by a factor of $\frac{1}{1-x\%}$. For example, for L-ROMP, this results in a cache size $\sim 1.35 \times$ the original size. We use this as the new cache size to update the cache hit rates at edge caches and origin caches (denoted by H_e and H_o , respectively) based on Figure 10 of [6].

Fraction of Requests Served by Cache Layers. A change in the cache hit rates in any layer would change the percentage of requests served by edge caches, origin caches and backend (denoted by S_e , S_o and S_b , respectively). At edge caches, we have $S_e = H_e$, at origin caches $S_o = (1 - H_e)H_o$ and $S_b = (1 - H_e)(1 - H_o)$ at the backend. Different sets of S_* means the re-distributions the load on different cache layers, and we use these values to analyze the load changes of different cache layers, changes to internal/external bandwidth and also the change in the distribution of the download latency. ¹⁰

Download Latency. We estimate the impact on download latency of changes to S_* by getting the distributions of download latencies from edge caches, origin caches and backend (denoted by L_e , L_o and L_b , respectively) and combining them to form one overall distribution using the new S_* . We obtain L_e and L_b from our previous work [20].11 Separately, we get origin cache to backend latency distribution from the Facebook study (Figure 7 of [6]) and subtract that (in a distributional sense) from L_b to get L_o . We then update L_* by taking ROMP or L-ROMP's decompression latency into account and shift the distribution uniformly. With both updated S_* and L_* , we can estimate the distribution of overall download latency L as follows. Let $L_*(x)$ be the probability of latency xms of the distribution L_* , we have $L(x) = S_e L_e(x) + S_o L_o(x) + S_b L_b(x)$. We can then enumerate on x to get the entire distribution of L.

		11
Compression	ROMP 13%	L-ROMP 26%
Effective Cache Size Hit Ratio Increase	1.15×	1.35×
Edge Cache	1.1%	2.5%
Origin Cache	1.6%	3.8%
Reduction in Requests to Backend	4.9%	11.4%
Reduction in Bytes Sent to Edge	15.2%	30.5%
Reduction in External Bandwidth	0.0%	15.5%

Fig. 11: Estimated collateral benefits from deploying ROMP in the Facebook photo caching stack.

b) Results: We now present the benefits of deploying ROMP.

Cache Hit Rates. Figure 11 shows how deploying ROMP on the Facebook photo caching stack would change the effective cache sizes and how this would affect cache hit rates. For instance, using L-ROMP would result in a 2.5% increase in the hit rate at the edge caches, and a nearly 4% increase in hit rate at the origin caches. In turn, these increases in the hit ratio can (1) reduce the number of requests to the storage backend, (2) reduce the bandwidth used between the storage backend and users, and (3) decrease latency for user requests [6]. We examine the effects of our schemes on each of these goals in turn.

Fewer Requests To The Storage Backend. Backend storage for images typically uses hard drives, which are capable of serving a small number of requests per second. For instance, a typical 4TB disk holding a large number of images is capable of a maximum of 80 Input/Output Operations Per Second (IOPS) while keeping per-request latency acceptably low [3]. As a result, one goal of an image caching stack is to reduce the number of requests to the backend storage system. Reducing requests allows images to be moved from hot storage with a high effective replication factor to warm storage with a lower effective replication factor sooner because the request rate would drop to what the warm storage system could handle sooner [3]. Figure 11 shows the reduction in requests to the backend. L-ROMP, for instance, would reduce requests to the backend by over 10%. The reduction comes from the hit rate increases in the caches.

Fewer Bytes To The Edge and Externally. One of the primary goals of Facebook's edge cache is to reduce the bandwidth required between it and the origin cache [6]. ROMP reduces the required bandwidth in two ways when deployed on the edge. First, our recompressed images are smaller than their JPEG Optimized counterparts. This results in a reduction in bandwidth proportional to the compression ratio. Second, the increased cache hit ratio would lead to fewer misses in the edge cache that need to be filled from

 $^{^{10}}$ We use S_* to collectively denote S_e , S_o , and S_b .

¹¹ This study measured the distribution of latencies for Facebook (and other photo providers) by downloading small images from several hundred PlanetLab sites and several thousand RIPE Atlas sites. We extend its results to what we would expect for larger images by using the reported time-to-first-byte latency and the transfer rate of the rest of the bytes. This will slightly over inflate the latency because the transfer rate of the slow start phase in TCP is generally slower than the congestion avoidance phase. But, we expect this effect to be small and believe our estimates are representative.

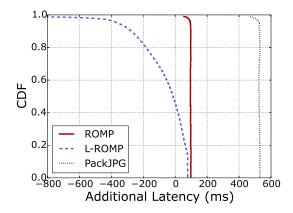


Fig. 12: Complementary cumulative distribution function (CCDF) on latency difference of deploying ROMP, L-ROMP and PackJPG.

the origin cache or the backend. The combination of effects is shown in Figure 11. L-ROMP, for instance, would *reduce* the bandwidth between the edge and origin by 30.5%.

An additional benefit of using L-ROMP arises from the fact that the image delivered to the user is often of smaller size than the uploaded image. Thus, it can reduce the data consumption of mobile devices as well as decrease the amount of external bandwidth of the service. This reduction is directly proportional to the lossy savings of those schemes, *i.e.*, their compression ratio without the normal ROMP component (Figure 11).

Latency Effects. One of the goals of a photo caching stack is to decrease the latency for users to download photos. The expected latency effects of deploying ROMP in a photo caching stack are complex and our objective was for them to make download latency no worse, and ideally better. The decoding time from ROMP would contribute additional latency to every request. But, it would also reduce latency in two ways. First, the increased hit rates at the caches would result in more requests being served by caching layers closer to the user. Second, the decrease in image size with L-ROMP requires fewer data transfers, thereby reducing overall download times.

Figure 12 shows the estimated latency of downloading a 2048×1536 image. We see that ROMP has a negligible effect on latency and L-ROMP reduces latency above the 40^{th} percentile. For the tail of the distribution above the 90^{th} percentile, L-ROMP can reduce latency by more than 500ms. This gain comes almost entirely from L-ROMP's reduction in image sizes; we also estimated the latency effect for L-ROMP cache hit rates without the image size reduction and saw a curve very similar to ROMP. The reason the increased cache hit rates do not have a noticeable impact is that the Facebook stack is well provisioned, *i.e.*, adding extra capacity has a small effect [6].

Above we mainly focused on deploying ROMP to the edge cache, the latency effect of deploying ROMP to the transcoder tier can be implied: the additional decoding latency would only be added to the requests served by the backend, so we observe similar latency effect above the 70th percentile (tail 30%), but lower latency for other percentiles. Photo sharing services work hard on optimizing the tail latency, and thus low complexity codecs are required as well [7]. Our analysis shows that (high complexity) PackJPG inflates the latency of the fastest 40% of downloads by more than 50%. Even though the decompression latency is incurred only for cache misses, we still see significant impact on the overall latency distribution: ~80% of the distribution incurs more than 150ms additional latency.

We also estimated the collateral benefits of deploying ROMP for photo sharing services that are not as well provisioned as Facebook, *e.g.*, services with limited cache sizes. For such services we see slightly larger improvements in all metrics, but we omit details due to space constraints.

V. RELATED WORK

This section explains how our approach relates to prior work in compressed storage systems, photo compression, and photo-sharing architectures.

Compression in Storage Systems. The use of compression for improving the efficiency of storage systems dates back several decades. These involve techniques for achieving compression in file systems such as [21], [22], [23], [24], in databases [25], [26] or for unstructured inputs [27]. ROMP is inspired by this line of work, especially the idea of "online compression" [22], [21], [23], but focuses on a relatively new class of large-scale storage systems specifically designed for photos, whose requirements and workloads are different than those considered by prior works. Unlike file or database compression systems, ROMP must compress already compressed objects, leveraging the observation that large coding tables can provide compact storage across the entire storage system (which file and database compression systems can leverage, but, to our knowledge, do not). In addition, our approach requires reasoning about performance impacts across globally distributed photo stack.

Photo Compression. Compression methods for photosharing services need to provide high compression and low complexity. Generic file compression techniques like gzip and bzip2, that do not leverage specific properties of images, can only provide negligible compression for photos beyond JPEG. The same is true of deduplication, which has received significant attention recently [28], [29], [30], [31], [32], [33]. We validated this experimentally on the FiveK image set and found $\leq 0.5\%$ compression for all generic schemes we tried: gzip, bzip2, xz, fixed-block deduplication, and variable-block deduplication.

Several papers have explored JPEG compression. Some of them focus on compressing JPEG losslessly [34], [35], [36], [37], [38]. However, as shown in Section IV, they either cannot achieve as high compression as ROMP, or have much higher complexity. JPEG lossy compression methods include transcoding from JPEG to another format (e.g., WebP [39] or JPEG2000 [4]) and transcoding to JPEG with lower quality or resolution. The former introduces high complexity [39], [4] and thus is not a viable option. Transcoding to JPEG but with lower quality and lower resolution often introduces significant degradations in quality [40], while L-ROMP degrades more gracefully than these approaches.

Recently, there have been several proposals for compressing photo storage based on analyzing higher-level structures (objects, landmarks) in similar images [41], [42], [43], [44]. Because they have to recognize such structural similarity, these techniques generally have much higher complexity; it is also not clear that their quality degradations are acceptable.

ROMP outperforms other lossless JPEG compression schemes by occupying a unique point in tradeoff between compression and complexity with high compression and low complexity. L-ROMP is inspired by prior work on thresholding [12], [45], [46], but differs from them in only introducing perceptually lossless changes and in its focus on low complexity as the design constraint.

Other Related Work. Researchers have also explored several complementary aspects of photo service stacks: Haystack [7] is used for image storage at Facebook and contains optimized metadata storage to reduce photo fetch latency; Huang et al. [6] present a measurement study of the efficacy of Facebook's distributed photo caching architecture which resembles Figure 2; and f4 [3] is a storage system for photos and other binary objects that are infrequently accessed. ROMP is complementary to this body of work; it can be used on Haystack or f4, and can improve caches in Facebook.

VI. CONCLUSION

Motivated by the need for additional tools for managing storage in large photo sharing services, this paper explores the problem of image recompression in these services and proposes two low complexity recompression schemes, ROMP and L-ROMP, that produce perceptually lossless compression with gains of 15-28%. Compression gains of this magnitude can substantially reduce storage requirements at these services. In addition, they increase cache hit ratios, reduce requests to the backend, reduce download latency and download sizes, and reduce wide area network traffic.

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