Large-Scale Analysis of the Docker Hub Dataset

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***Abstract*—Docker containers have become a prominent solution for supporting modern enterprise applications due to the highly desirable features of isolation, low overhead, and efficient packaging of the execution environment. Containers are created from images which are shared between users via a Docker registry. The amount of data Docker registries store is massive; for example, Docker Hub, a popular public registry, stores at least half a million public images. In this paper, we analyze over 167 TB of uncompressed Docker Hub images, characterize them using multiple metrics and evaluate the potential of file-level deduplication in Docker Hub. Our analysis helps to make conscious decisions when designing storage for containers in general and Docker registries in particular. For example, only 3% of the files in images are unique, which means file-level deduplication has a great potential to save storage space for the registry. Our findings can motivate and help improve the design of data reduction, caching, and pulling optimizations for registries.**

I. Introduction

Recently, *containers* [1] have gained significant traction as an alternative to virtual machines [2] for virtualization both on premises and in the cloud. Polls suggest that 87% of enterprises are in the process of adopting containers, and that containers are expected to constitute a lucrative $2.5 billion market by 2020 [3]. In contrast to Virtual Machines (VMs), containers share the same kernel but are isolated in terms of process visibility (e.g., via namespaces [4]) and resource usage (e.g., via control groups [5]). Containers require fewer memory and storage resources, start faster, and typically incur less execution overhead than VMs [6]–[8].

A driving force for fast container adoption is the popular Docker [9] container management framework. Docker combines process containerization with convenient packaging of an application's complete runtime environment in *images*. For storage and network efficiency, images are composed of independent, shareable *layers* of files. Images and their corresponding layers are stored in a centralized *registry* and accessed by clients as needed. Docker Hub [10] is the most popular registry, currently storing more than 500,000 public image repositories comprising over 2 million layers. The size of the registry is steadily increasing. Over a period from June to September 2017, we observed a linear growth of the number of images in Docker Hub with an average creation rate of 1,241 public repositories per day. We expect this trend to continue as containers gain more popularity.

While the massive image dataset presents challenges to the registry and client storage infrastructure, storage for containers has remained a largely unexplored area. We believe one of the prime reasons is the limited understanding of what data is stored inside containers. This knowledge can help improve the container storage infrastructure and ensure scalability of and fast accesses to the registry service. Existing work has focused on various aspects of containerization [11]–[16]. However, the registry and its contents have yet to be studied in detail.

In this paper, we perform the first, comprehensive, large-scale characterization and redundancy analysis of the images and layers stored in the Docker Hub registry (§II). We download all `latest` publicly accessible images (as of May 2017), which amount to 47 TB of image data (§III). Based on that dataset, we analyze traditional storage properties, such as file count, data compression ratios, directory depths, as well as Docker-specific properties, e.g., the number of layers per image, image popularity, and the amount of layer sharing. Furthermore, we investigate the potential for data reduction in the Docker registry by using file-level deduplication.

Our analysis reveals several interesting insights (§IV). First, the majority of layers are small in size and show a low compression ratio. 50% of the layers are smaller than 4 MB which holds both for compressed and uncompressed layers, and the median layer compression ratio is 2.6. As compression is computationally intensive, storing small layers in the registry uncompressed can improve latency during pulls as layers do not have to be uncompressed locally anymore. Second, we find that only around 3% of the files are unique while others are redundant copies. This suggests that file-level deduplication has a great potential to save storage space for large-scale registries.

We also find that image accesses are skewed towards a small number of popular images. Specifically, 90% of repositories are pulled less than 300 times since creation, while the largest number of pulls we record for an image is over 600 million. This suggests that image caching is a viable improvement for the registry. Our analysis provides a first insight into the Docker image dataset, which can help improve the design of current data reduction, caching, and pulling optimizations for container registries.

II. Background

Container-based virtualization (such as Linux Containers (LXC) [17]) has emerged as a lightweight virtualization alternative. Compared to Virtual Machine based server virtualization technologies (e.g., VMware [18] or Xen [19]), container virtualization works at the operating system level. Containers share the same kernel which improves startup

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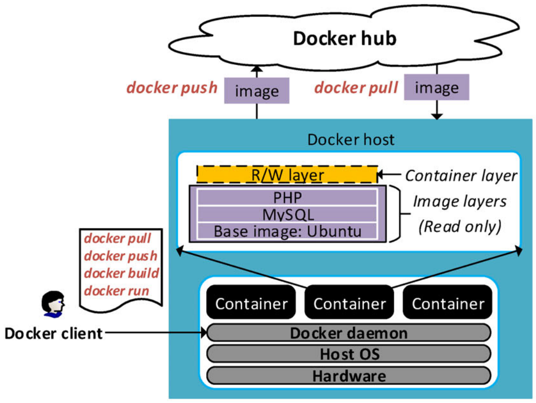


Fig. 1. Docker ecosystem

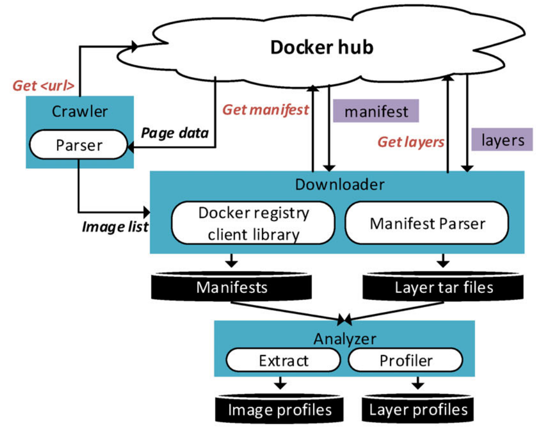


Fig. 2. Crawler, Downloader, and Analyzer

times and significantly reduces the storage and memory overhead [20].

A. Docker

Docker is a popular containerization framework, which extends LXC with higher level APIs and additional functionality. It automates the deployment of applications inside Linux containers, and provides the capability to package an application with its runtime dependencies into a container [14].

As shown in Figure 1, the Docker ecosystem consists of several components. Users interact with Docker via the Docker *client*, which sends commands to the Docker *daemon*. The daemon is responsible for *running* containers from locally available images. Additionally, the daemon supports *building* new images and *pushing* them to a Docker *registry*. When a user wants to launch a container from an image that is not available locally, the daemon *pulls* the required image from the registry.

B. Docker images and layers

At the center of Docker is the concept of container images for packaging, distributing, and running applications. Docker images consist of a series of individual *layers*. A layer contains a subset of the files in the image and often represents a specific component/dependency of the image, e.g., a library. This modular design allows layers to be shared between two images if both images depend on the same component.

Image layers are read-only. When users start a container, Docker creates a new writable layer on top of the underlying read-only layers as shown in Figure 1. Any changes made to files in the image will be reflected inside the writable layer via a copy-on-write mechanism. This leaves image layers unmodified throughout the lifetime of a container and enables layer sharing. Docker supports multiple storage drivers, e.g., Aufs and Btrfs, which efficiently combine read-only and writable layers in a single file-system namespace and support copy-on-write [21]. The writable layers are discarded when the container is deleted.

An image is represented by a *manifest* file, which contains a list of layer identifiers (digests) for all layers required by the image. Moreover, it describes the various parameters of a Docker image, such as the target hardware platform and environment settings.

C. Docker registry

The Docker registry is a platform for storing and sharing container images. It stores images in *repositories*, each containing different versions of the same image. Image layers are stored as compressed archival files and image manifests as JSON-based files. Docker Hub is one of the most popular public registries, supporting both public and private repositories, where users can upload, search, and download images [10]. In Docker Hub, the user repositories are namespaced by user name, i.e., `<username>/<repository name>`, while the official repositories, which are directly provided by Docker Inc. and partners, are called `<repository name>`.

III. Methodology

Our image analysis methodology consists of three steps (see Figure 2): i) crawl Docker Hub to list all repositories; ii) download the latest version of an image and all referenced layers from each repository based on the crawler results; iii) decompress and analyze images and layers.

A. Crawler

To download a particular image, the name of the repository which the image belongs to needs to be provided. The crawler is responsible for generating a list of repositories for the downloader.

Public repositories in Docker Hub (i.e., the repositories that anyone can pull from) are divided into official repositories, served by the Docker Hub partners, and non-official repositories, provided by regular users and third-party organizations. The number of official repositories is less than 200, while, the majority of repositories in Docker Hub are non-official (over 400,000). Listing non-official repositories requires web crawling because Docker Hub does not support an API to retrieve all repository names.

Our crawler utilizes the Docker Hub's Web-based search engine to find all available repositories. As the name of non-official repositories is comprised of the user name and the repository name separated by a "/", we can search for "/" and obtain a list of all non-official repositories. The Crawler downloads all pages from the search results and parses the web content to build a list of all non-official repositories. We ran the crawler on May 30th, 2017 and it delivered a list of 634,412 repositories. After removing duplicate entries (introduced by Docker Hub indexing logic), the final repository list consists of 457,627 distinct repositories.

B. Downloader

Images in Docker Hub repositories are labeled with *version tags* to track different image versions. If a user does not provide a tag when pulling an image, Docker client pulls the `latest` tag by default. In this work we focus on downloading images with the `latest` tag to make the analysis more feasible. We plan to extend our analysis to other image tags in the future.

Instead of using the Docker client to download images, we implement our own downloader, which calls the Docker registry API directly [22] to download manifests and image layers in parallel. Note that we only download unique layers. Our downloader runs significantly faster than a `docker pull`-based downloader which performs many other operations in addition to downloading the image. For example, it automatically extracts each layer's tar archive file and creates the corresponding read-only snapshot using the configured Docker storage driver. This not only takes considerable amount of time but also leads to overly high storage space utilization. Furthermore, the local storage format of Docker images makes it difficult to analyze the contents of each layer separately. Our downloader can download multiple images simultaneously and fetch the individual layers of an image in parallel. Layers are transferred as gzip compressed tar archives.

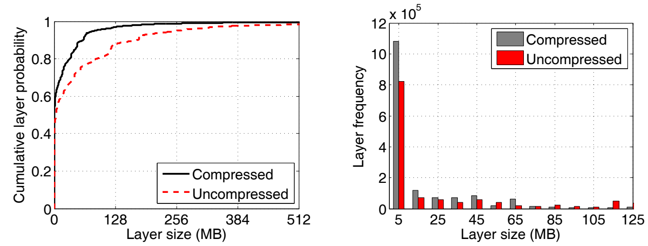
The whole downloading process took around 30 days. Overall, we downloaded 355,319 images, resulting in 1,792,609 compressed layers and 5,278,465,130 files, with a total compressed dataset size of 47 TB. A total of 111,384 images could not be downloaded due to two reasons: 1) 13% of these images required authentication; 2) 87% of these images did not have a `latest` tag.

C. Analyzer

The analyzer extracts the downloaded layers and analyzes them along with the image manifests. For each image, it creates an image profile and individual layer profiles, which contain metrics for the whole image and its individual layers, respectively.

a) Layer profile: To produce the layer profile, the analyzer first decompresses and extracts each layer tarball to a layer directory. Then, it recursively traverses each subdirectory and obtains its metadata information. A layer profile contains the following information:

1) Layer metadata: { layer digest; layer size, which is the sum of contained file sizes (FLS); compressed layer size, which is the size of compressed layer tarball (CLS); directory count; file count; max. directory depth }



(a) CDF of layer sizes (b) Histogram of layer sizes

Fig. 3. Layer size distribution

2) Compression ratio: { FLS-to-CLS; }
3) Directory metadata (for every directory in the layer): { directory name; directory depth; file count; }
4) File metadata (for every file in the layer): { file name; file digest; file type (identified by magic number); file size; }

b) Image profile: To create the image profile, the analyzer parses the manifest and obtains the configuration information such as OS and target architecture. Further, once individual layers are analyzed, the analyzer builds the image profile by including pointers to its layer profiles. An image profile consists of:

1) Image metadata: { image name; sum of containing file sizes (FIS); compressed image size (CIS); directory count; file count; }
2) Compression ratio: { FIS-to-CIS; }

IV. Dataset Characterization

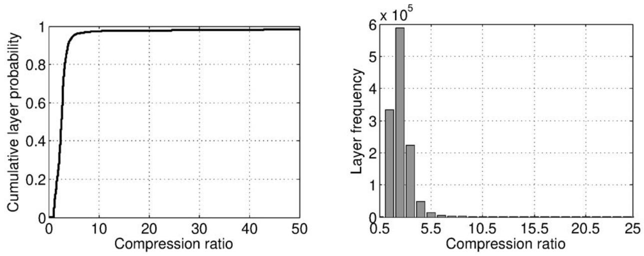
In this section we carry out our analysis of the Docker Hub dataset by characterizing layers, images, and files. While overall we are interested in its general structure, we also analyze specific properties that allow us to draw conclusions regarding the caching, compression, and resource provisioning for Docker images.

A. Layers

We start by analyzing layers in terms of size and compressibility, file and directory counts, and directory depths.

a) Layer sizes: We characterize layer sizes using two different metrics: 1) compressed layer size (CLS)—the format a layer is stored in the registry or transferred to a client; and 2) files in layer size (FLS)—the sum of the sizes of the uncompressed files contained in the layer. Figure 3(a) shows the CDF of the two metrics.

We see that 90% of the layers are smaller than 177 MB in uncompressed format and smaller than 63 MB in compressed format. Interestingly, about half of the layers are smaller than 4 MB, independent of the format. That means that the registry stores a large number of small layers which do not benefit from compression. To analyze the frequencies, we zoom into the 0–128 MB range (see Figure 3(b)). More than 1 million and 800,000 layers are smaller than 5 MB in compressed and uncompressed format, respectively. Beyond that, the frequency drops rapidly and we only see around 100,000 layers between 5 MB and 15 MB.



(a) CDF of compression ratio (b) Histogram of comp. ratios

Fig. 4. Layer compression ratio distribution

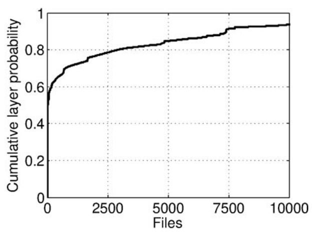


Fig. 5. File count distr.

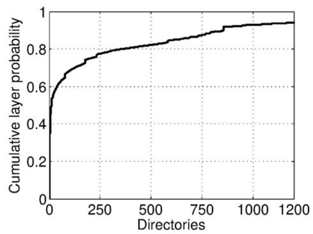


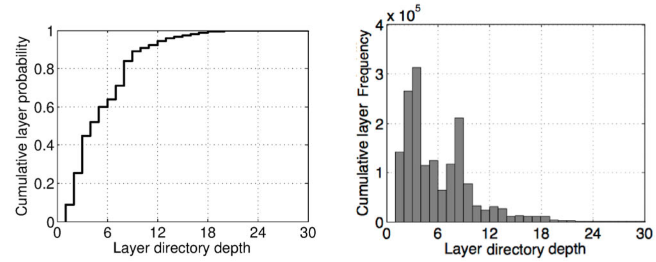
Fig. 6. Dir. count distr.

To further study the sizes and the impact of compression, we calculate the FLS-to-CLS compression ratios (see Figure 4(a)). 90% of layers have a FLS-to-CLS ratio less than 4 and the median compression ratio is 2.6. The largest compression ratio is 1026. Looking at the histogram in Figure 4(b), we see that around 600,000 layers have a compression ratio of between 2 and 3 while more than 300,000 between 1 and 2.

Our size analysis reveals an interesting trade-off. Compression is computationally expensive and is one of the major sources of latency when pulling an image from Docker Hub [14]. As the majority of layers are small and have low compression ratios, it can be beneficial to store small layers uncompressed in the registry to reduce pull latencies.

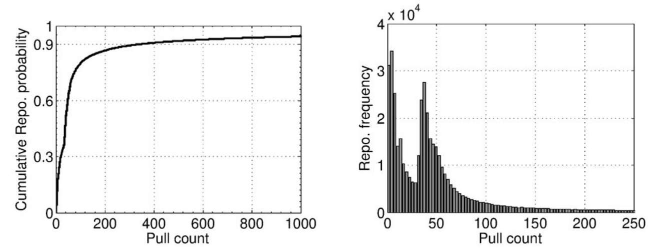
b) File and directory counts: Next, we look at file and directory metrics in layers. Figures 5 and 6 show the CDFs of file and directory counts in all layers, respectively. The results show that 90% of layers contain less than 7,410 files while half of the layers have less than 30 files. We also found that 27% of the layers only have a single file while 7% even showed no files at all. We currently do not know the exact reason for the layers without files. One theory is that these layers use Docker volumes (i.e., host file system directory '/var/lib/docker/volumes/' on Linux) to store all required files (including executables). On the other hand, the largest layer contains 826,196 files and was part of a Debian image. For directories, 90% of the layers have less than 826 directories and half of the layers consist of less than 11 directories. We again observe a wide range with a minimum of a single directory and a maximum of 111,940. The layer with the most directories was part of the *conjurinc/developer-quiz* image.

Besides the count, we also calculate the maximum directory depth for each layer (Figure 7(a)). Around 90% of all layers have a directory depth less than 10 while for 50% of the layers, the directory depth is less than 4. The most frequent



(a) CDF of layers by layer directory depth (b) Histogram of layers by layer directory depth

Fig. 7. Layer directory depth distribution



(a) CDF of repositories by pull count (b) Histogram of repositories by pull count

Fig. 8. Repository popularity distribution

directory depth is 3 with 313,000 layers showing this depth value (Figure 7(b)).

This analysis shows that the majority of layers consist only of a small number of files and does not contain deeply nested directory hierarchies. Hence, except for few outliers, unpacked layers do not require a large amount of metadata from the storage system.

B. Images

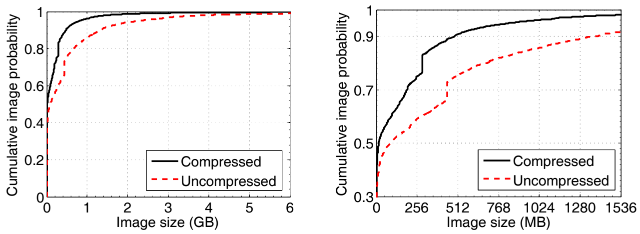
Next, we study images in terms of their popularity, size and their use of layers.

a) Image popularity: We start by analyzing image popularity. Figure 8 shows the repository popularity distribution in terms of the pull count of individual images. The CDF in Figure 8(a) reveals a large degree of skew in image pulls. In the median, images are only pulled 40 times while in the 90% percentile we see a pull count of 333. On the other hand, the largest pull count is more than 650M which is for the official *nginx* repository. This is followed by Google's *cadvisor* (434M pulls), *redis* (264M pulls), *ubuntu* (28M pulls) and GliderLabs' *registrator* (212M pulls).

Looking at the pull frequencies for repositories (see Figure 8(b)) confirms the skewness. We see that 31,200 of repositories are only pulled between 0 and 2 times while 34,100 repositories are pulled between 3 to 5 times. What is interesting is that there is a second peak around a pull count of 37 which does not fit a heavy-tailed distribution.

The skewness of the two curves in Figure 8 suggests that Docker Hub is a good fit for caching popular repositories or images to reduce pull latencies.

b) Image size distribution: Similarly to layers, we also measure compressed image size (CIS), i.e. the sum of the sizes



(a) CDF of images by size (GB)

(b) CDF of images by size (MB)

Fig. 9. Image size distribution

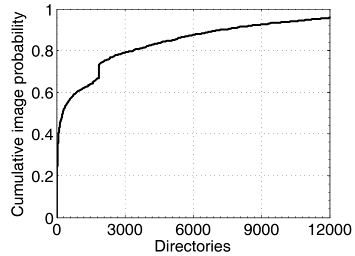


Fig. 11. CDF of images by directories

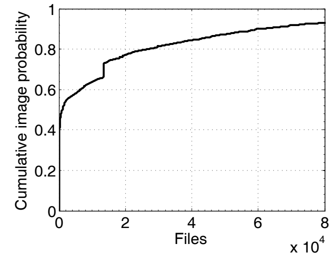
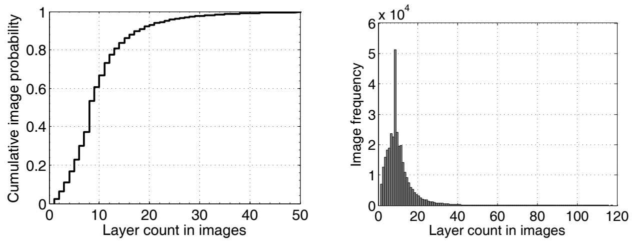


Fig. 12. CDF of images by files



(a) CDF of layer count in images

(b) Histogram of layer count in images

Fig. 10. Layer count

of the compressed image layers, and the sum of the sizes of files contained in the image (FIS). Figure 9(a) and 9(b) show the image size distributions at a coarse GB resolution and a finer resolution only covering images smaller than 1.5 GB.

90% of the images have an uncompressed size less than 1.3 GB while compressed images are less than 0.48 GB. In the median, this decreases to 94 MB and 17 MB, respectively. The largest uncompressed image is 498 GB which is a Ubuntu-based image. Figure 9 shows that the majority of uncompressed images in Docker Hub are small which aligns with the Docker philosophy to package software and distribute software in containers but include only its necessary dependencies.

c) Layer count distribution: As discussed in §II-B, images consist of a set of layers. It is important to understand the layer count of the images as previous work found that the number of layers can impact the performance of I/O operations [14]. Therefore, we count the number of layers per image and plot the CDF (see Figure 10(a)) and layer count frequencies (see Figure 10(b)) for all Docker Hub images.

The results show that 90% of the images have less than 18 layers while half of the images have less than 8 layers. 8 layers is also the most frequent layer count per image with 51,300 images consisting of exactly 8 layers. The maximum layer count is 120 in the *cfgarden/120-layer-image*. We also find that there are 7,060 images that consist of only a single layer.

d) Directory and file count distribution: Lastly, we look at directory (see Figure 11) and file counts (see Figure 12) in images to determine if deploying images requires handling of large amounts of metadata. Looking at directories, we see that 90% of images have less than 7,344 directories while the median is at 296. For files, 90% of images have less than 64,780 files with a median of 1,090.

This is consistent with our analysis of layer-based file and directory counts and the number of layers per image. Again, we conclude that most images do not require an extensive amount of metadata when being deployed as file and directory counts are low except for relatively rare outliers.

C. Files

After analyzing layers and images, we conducted a deeper analysis on the files that are stored in containers. Specifically, we characterize files in terms of size and type. Based on this characterization, we create a three-level classification hierarchy as shown in Figure 13. At the highest level, we created two categories: *Commonly used file types* and *non-commonly used file types* based on the total file size and file count for each type. Totally, we got around 1,500 types after analyzing our whole dataset. We found that only 133 file types take up more than 7 GB individually and occupy the most capacity (98.4%, with 166.8 TB) totally. We put these 133 file types into commonly used file type group and the remaining files into non-commonly used file types. Our further classification expands on the 98.4% commonly used file types.

At the second level of the hierarchy, we clustered commonly used file types based on the major file format, usage, or platform involved by each file type. We identified commonly used file types relevant to *EOL (executable, object code, and libraries)*, *source code*, *scripts*, *documents*, *archival*, *images*, *databases*, and *others*.

At the third level, we present the specific file types which take a large percentage of storage space.

a) Common used file types: Figure 14 shows the 8 type groups in terms of file count and capacity. 13%, 11%, and 9% of files are source code, EOL, and scripts. EOL files occupy the most capacity (37%).

We also see that 44% of files are document files such as Microsoft office files, LaTeX files, etc. Only 4% of files are image data files, e.g., PNG, JPEG, etc. Besides, we found a small amount of video files like AVI, MPEG, etc.

To find how file type relate to file size, we calculated the average file size by file type group as shown in Figure 15. We see that Database files are much bigger (978.8 KB) than the files within other type groups. The average size of EOL and Archival files are around 100 KB.

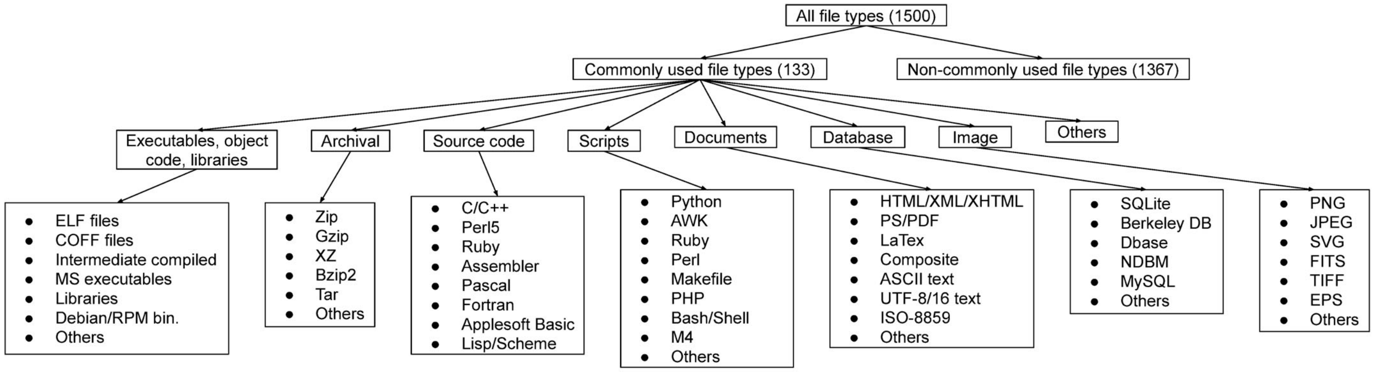
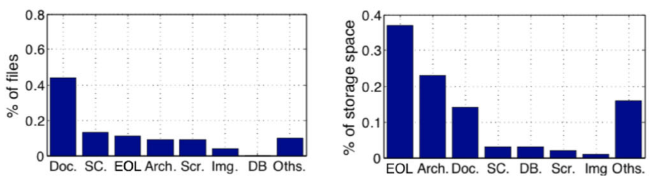


Fig. 13. Taxonomy of file types.



(a) File count (in %) by file type group. (b) Capacity (in %) by file type group.

Fig. 14. Commonly used file types

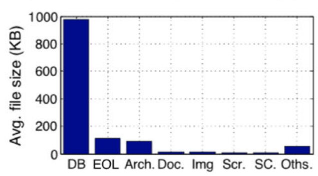
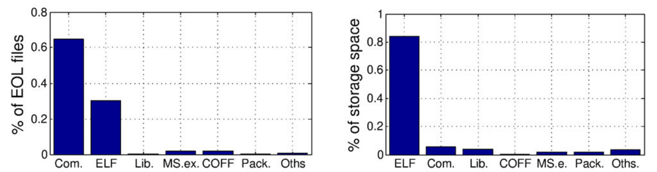
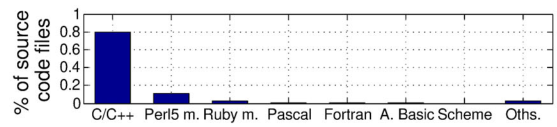


Fig. 15. Average file size by file type group.

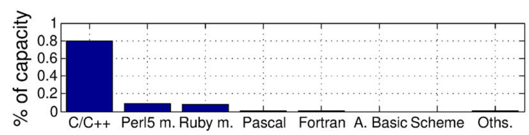


(a) File count (in %) by file type. (b) Capacity (in %) by file type.

Fig. 16. EOL files



(a) File count (in %) by file type.



(b) Capacity (in %) by file type.

Fig. 17. Source codes

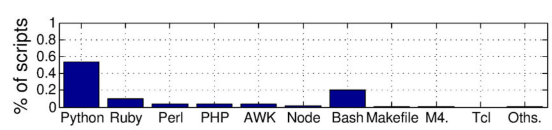
b) Executable, object code, and libraries (EOL): Based on the third-level classification, we further investigate the file size and file count by specific file types. We start with EOL group which contains the following types: ELF files, COFF files, intermediate representation that can be executed by a virtual machine, Microsoft executables, Debian/RPM binary packages, libraries, and other EOL files.

Figure 16 shows file type distribution in terms of file count and capacity for EOL type group. We see that majority of EOL files are ELF and intermediate representations (shown as "Com." in the Figures). ELF files mainly contain ELF relocatables, shared objects, and executables. Intermediate representations mainly contain Python byte-compiled files (majority), compiled java class, and terminfo compiled files. Although intermediate representations take up to 64% of EOL files, 30% of EOL files occupy 84% of storage space consumed by the EOL group. This is because average ELF file size is 312 KB while the average intermediate compiled file size is 9 KB. In addition to ELF files and representations, we found Microsoft executables (2%) and Mach-O files (<0.01%) in the EOL group.

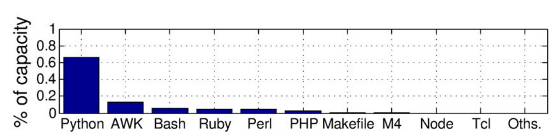
We conclude that among all file types, ELF files occupy most capacity. There are large amount of intermediate representations but they take much less storage space.

To know what kind of libraries are used in Docker containers, we categorized the libraries. The most popular libraries we found are: the Palm OS dynamic library, the OCaml library, and the GNU C library.

c) Source code (SC.): Next, we inspect what kind of languages are commonly used by Docker developers. Figure 17 shows 7 major types of source codes in our dataset: C/C++,

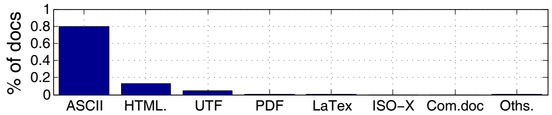


(a) File count (in %) by file type.

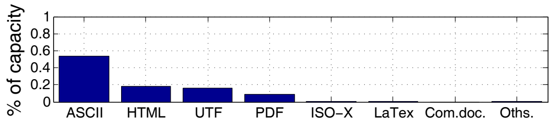


(b) Capacity (in %) by file type.

Fig. 18. Scripts

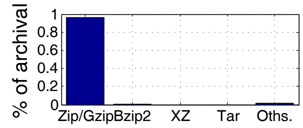


(a) File count (in %) by file type.

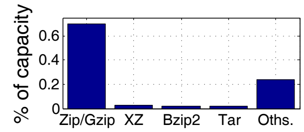


(b) Capacity (in %) by file type.

Fig. 19. Documents

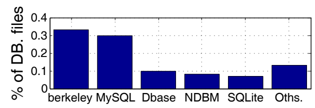


(a) File count (in %) by file type.

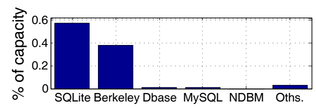


(b) Capacity (in %) by file type.

Fig. 20. Archival files



(a) File count (in %) by file type.



(b) Capacity (in %) by file type.

Fig. 21. Databases

Perl5 module, Ruby module, Pascal, Fortran, Applesoft basic, and Lisp/Scheme. 80.3% of source files are C/C++ sources which take about 80% of storage space within the source code group. Perl5 module source code and Ruby module source code have an almost similar percentage in terms of file count (9% for Perl5 module source and 8% for Ruby module source) but occupy different percentage in terms of capacity (11% for Perl5 modules and 3% for Ruby modules).

d) Scripts (Scr.): Compared to the source code group, we found a larger variety of scripting languages used. Our script group includes Python scripts, AWK, Ruby, Perl, PHP, Make, M4 macro processor, node, Tcl, Bash/shell, and others. We see in Figure 18 that more than half of the scripts are Python-based script (53.5%), which take around 66% of storage space occupied by all scripts. Another commonly used script type are Bash/shell scripts (20%) which only occupy 6% of storage space. 10% of scripts are Ruby scripts which take around 5% of storage space in the scripts group.

e) Documents (Doc.): As discussed before, 44% of files are documents which take up to 14% of storage space. As shown in Figure 19, we see that majority of documents are text files including ASCII text (80%), UTF8/16 text (5%), and ISO-8859 text (0.4%), which take up to 70% of storage space occupied by documents. Note that these text files are *raw text files* since we already filter the text based well-known file types, such as scripts and source code.

Another observation is that XML/HTML/XHTML documents are the second most commonly used documents (13%), which take up over 18% of storage space occupied by documents. Moreover, we found a small amount of PDF/PS documents and LaTeX files in our dataset.

f) Archival (Arch.): The archival file group, takes up to 23% of capacity and is the second most commonly used file type group. To figure out what kind of archival files are used in Docker containers, we look at the archival file type distribution as shown in Figure 20. We see that majority of archival files are Zip/gzip files (96.3%) which take up to 70% of storage space within the archival files, meaning that Zip/gzip files have a lower average file size. We calculated the average file size for each file type. The average file sizes are 67 KB, 199 KB, 466 KB, and 534 KB for Zip/gzip, bzip2, tar, and xz files, respectively.

g) Databases (DB.): Interestingly, we found a certain amount of database related files in our dataset. As shown in Figure 21, over half of the database related files are Berkely DB (33%) and MySQL (30%) files, but these types take up less than 40% of capacity occupied by database related files. 7% of database related files are SQLite DB files, which take up over 57% of capacity.

This finding means that Docker developers run databases inside Docker containers. The most frequently used databases are Berkeley DB and MySQL, while the database using most of capacity is SQLite. We currently do not know whether these databases are mainly read-only or are also used for write-based workloads. This might cause performance problems in some situations due to the copy-on-write overhead of the storage drivers [21].

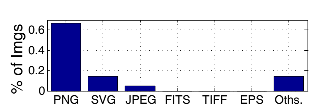
h) Images (Img.): We also found some image data files, such as PNG, JPEG, SVG, etc. in Docker container images. As shown in Figure 22, more than half of image files are PNG files (67%), which take about 45% of capacity occupied by image files. The second most commonly used image files are JPEG files which take up around 20% capacity.

V. Deduplication Analysis

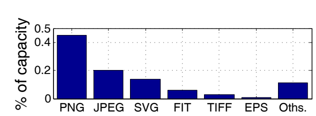
In this section, we investigate the potential for data reduction in the Docker registry by analyzing the efficacy of layer sharing and file-level deduplication.

A. Layer sharing

Compared to other existing containerization frameworks [23], [24], Docker supports the sharing of layers among different images. To study the effectiveness of this approach, we compute how many times each layer is referenced by images. Specifically, we analyze all image manifests and count



(a) File count (in %) by file type.



(b) Capacity (in %) by file type.

Fig. 22. Images

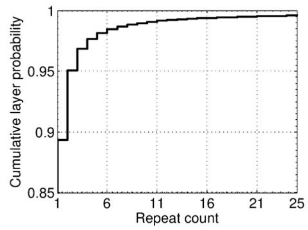


Fig. 23. CDF of layer reference count

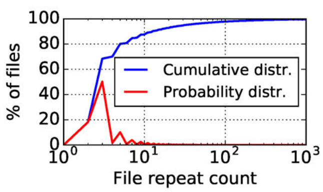


Fig. 24. File repeat count distribution.

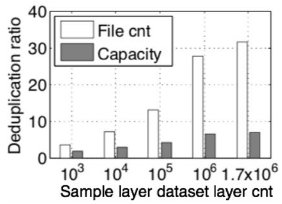


Fig. 25. Deduplication ratio growth.

for each layer, how many times it is referenced by an image. Figure 23 shows that around 90% of layers are referenced by a single image, an additional 5% are referenced by 2 images, and less than 1% of the layers are shared by more than 25 images.

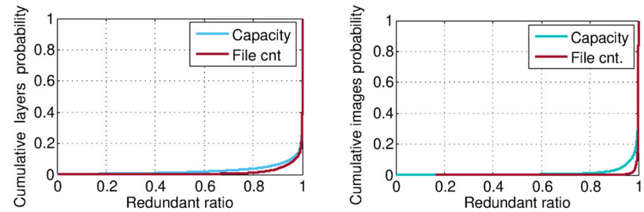
Interestingly, there is one layer that is referenced by 184,171 images. Further analysis reveals that this is an empty layer. The presence of an empty layer in an image can be explained by the fact that during the image build, Docker creates a new layer for every `RUN <cmd>` instruction in the Dockerfile [25]. If the `<cmd>`, which can be an arbitrary shell command, does not modify any files in the file system, an empty layer is created. The next 5 top-ranked layers by reference count are included in 29,200 – 33,413 images. Specifically, one layer contains a whole `Ubuntu 14.04.2 LTS` distribution, one layer contains a `sources.list` file for `apt`, and one layer contains binaries and libraries needed for `dpkg`. The other two layers are related to cowsay, a program that can generate ASCII pictures of a cow with a message [26]. One layer contains a whole installation package for `cowsay 3.03` while the other layer only contains the binaries for cowsay.

From the above data we can estimate that without layer sharing, the Docker Hub dataset would grow from 47 TB to 85 TB, implying a **1.8**× deduplication ratio provided by layer sharing.

B. File-level deduplication

Next, we calculate the deduplication ratio in terms of file count and capacity for the complete dataset. After removing redundant files, there are only 3.2% of files left, which in total occupy 24 TB, resulting in deduplication ratios of **31.5**× and **6.9**× in terms of file count and capacity, respectively.

We further analyze the repeat count for every file (see Figure 24). We observe that over 99.4% of files have more than one copy. Around 50% of files have exactly 4 copies and 90% of files have 10 or less copies. The file that has the maximum repeat count of 53,654,306 is an empty file.



(a) CDF of cross layer file duplicate ratio. (b) CDF of cross-image file duplicate ratio.

Fig. 26. Cross layer file duplicates and cross image file duplicates

Around 4% of empty files are `__init__.py` files, which make Python treat a directory as containing packages and are usually empty. Other frequent empty files include `lock` or `.gitkeep` files.

We also analyze the top five most frequently repeated files which repeat between 3,338,145 and 11,847,356 times. Specifically, two files `libkrb5-3:amd64.postrm` and `libkrb5-3:amd64.postinst` are two Kerberos runtime libraries for `dpkg`. Another two files are related to the `npm` package manager (`license` and `.npmignore`) and the last file, `dependency_links.txt`, contains a list of dependency URLs for Python.

This shows that there is a high file-level redundancy in Docker images which cannot be addressed by the existing layer sharing mechanism. Hence, there is a large potential for file deduplication in the Docker registry.

C. Deduplication ratio growth

To further study the potential of file-level deduplication, we analyze the deduplication for an increasing number of files stored in the registry (see Figure 25). The x-axis values correspond to the sizes of 4 random samples drawn from the whole dataset and the size of the whole dataset.

We see that the deduplication ratio increases almost linearly with the layer dataset size. In terms of file count, it increases from **3.6**× to **31.5**× while in terms of capacity, it increases from **1.9**× to **6.9**× as the layer dataset grows from 1000 to 1.7 million layers. This confirms the high potential for file-level deduplication in large-scale Docker registry deployments.

D. Cross layer file duplicates

Based on the high deduplication ratio, we conclude that a large amount of files are shared between layers and the large potential from deduplication is due to large amount of file duplicates among layers. Cross layer file duplicates are files that are stored in more than one layer, which cannot be eliminated by the layer-level-sharing mechanism. This could be a common problem for layers in the Docker registry. For example, different developers may use the same libraries and build same executables in their layers. But only few files in their layers are different from each other, which makes their layers *different*.

Figure 26(a) shows the percentage of cross layer file duplicates for each layer. We find that 90% of layers contain more than 97.6% of files that are duplicated across layers. We

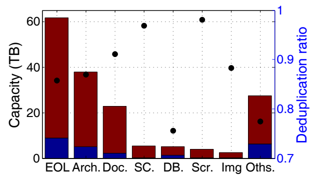


Fig. 27. Overall deduplication ratio.

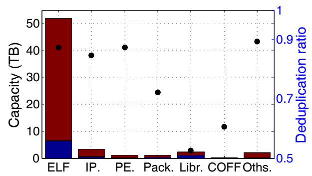


Fig. 28. Deduplication results for EOL files.

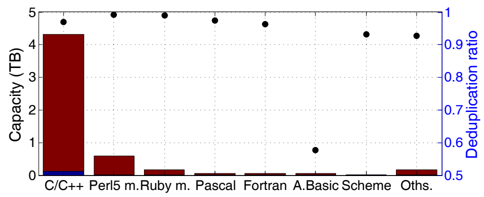


Fig. 29. Deduplication results for source codes.

also calculate the percentage of files that are duplicated across images. As shown in Figure 26(b), 90% of images contain more than 99.4% of files that are duplicated across images, indicating that majority of files are duplicated across different images and layers.

E. Deduplication by file types

To understand what are the file duplicates and why there are so many file duplicates, we look at the deduplication results from the perspective of file types. In this section, we present the deduplication results for common file types that occupy the most capacity.

Figure 27 shows deduplication results for the following type groups: EOL, archival, documents, source code, scripts, images, and databases. Note that the y-axes show the capacity occupied by different type groups and their deduplication ratios.

The overall deduplication ratio is 85.69%, and most of the type groups have a comparable ratio. For example, 86% of EOL files, which include executables, object files, and libraries, can be deduplicated at file-level. Source codes, scripts, and documents have the highest deduplication ratio (96.8% for source codes, 98% for scripts, and 92% for documents), which means that Docker developers are more prone to duplicate source code, scripts, and documents.

Next, we see that EOL files, archival, and images have a similar deduplication ratio of around 86%. Compared to other type groups, the redundant EOL files and archival files occupy over half of the capacity (51.4%). Database related files have the lowest deduplication ratio (76%), which contributes little to the overall savings.

a) Executable, object code, and libraries (EOL): We further calculate the deduplication ratio for specific file types in each common type group. We start from the EOL group since it occupies the most capacity and contributes a lot to the overall savings after deduplication.

Figure 28 shows the deduplication results for EOL files. We see that ELF files, intermediate representations, and PE files have the highest deduplication ratio (around 87%). Especially, the redundant ELF files occupy the most capacity (73.4%). Libraries and COFF files have the lowest deduplication ratio of 53.5% and 61% respectively.

We also calculate the deduplication ratio for each intermediate representation and libraries. We found that all the intermediate representations have a high deduplication ratio (greater than 77%). Especially, the redundant Python byte-compiled code take up to 67% of capacity occupied by intermediate representations. Although the overall deduplication ratio of the library group is lower, we observed that the GNU C/C++ library and the Palm OS dynamic library have a deduplication ratio of over 90%.

b) Source code (SC.): As discussed, Docker developers are more prone to replicate source code. To find out which kind of source codes are replicated frequently, we study deduplication on 7 common languages as shown in Figure 29.

We see that all the languages have a high deduplication ratio of over 90% except for Lisp/Scheme. In particular, redundant C/C++ source files take up over 77% of capacity occupied by source code files. To find out why there are so many duplicate C/C++ source files, we inspect those files and find a frequently reused sources related to Google Test [27], a cross-platform C++ test framework available on GitHub [27]. Interestingly, we also observe that there are a large number of repositories related to Google Test but there is no official repository. We suspect that many developers replicate open source code from external public repositories, such as GitHub, and store it in their container images. This could also explain why there are so many shared source code files across different images. Considering that Docker Hub allows developer to automatically build images from source code in external public repositories and automatically push the built image to their Docker repositories, we believe that replicated source code in different images is a common case in the Docker Hub registry.

VI. Related work

Due to its increasing popularity, Docker has recently received increased attention from the research community. Slacker [14] studied 57 images from Docker Hub for a variety of metrics. The authors used the results from their study to derive a benchmark to evaluate the push, pull, and run performance of Docker graph drivers based on the studied images. Compared to Slacker, our analysis focuses on the entire Docker Hub dataset. Anwar et al. [28] propose a new Docker registry design that employs a two-tier registry cache hierarchy. Bolt [29] presents a hyperconverged Docker registry to improve latency and throughput. However, both of these designs are based on workload traces and do not consider content and storage properties of images. Cito et al. [13] conducted an empirical study for characterizing the Docker ecosystem with a focus on prevalent quality issues, and the evolution of Docker files based on a dataset of 70,000 Docker files. However, their study did not focus on actual image data. Shu et al. [15] studied the security vulnerabilities in Docker Hub images based on a dataset of 356,218 images and found there is a strong need for more automated and systematic methods of applying security updates to Docker images. While the amount of images is similar compared to our study, Shu et al. focused on a subset of 100,000 repositories and different image tags in these repositories.

Dockerfinder [12] is a microservice-based prototype that allows searching for images based on multiple attributes, e.g., image name, image size, or supported software distributions. It also crawls images from a remote Docker registry but the authors do not provide a detailed description of their crawling mechanism. Bhimani et al. [11] characterized the performance of persistent storage options for I/O intensive containerized applications with NVMe SSDs. Unlike our study, their analysis is focused on the execution of containers rather than on their storage at the registry side. Skourtis et al. [30] looked at the deduplication ratio of 10,000 most popular images in Docker Hub to motivate the new approach to more efficient organization of Docker images. Our study focuses on wider and larger scale characterization of Docker images.

Future work In the future, we plan to extend our analysis to multiple versions of Docker images and study the dependencies among them. In addition, we will further analyze how layer hierarchy and compression methods impact access latency. Moreover, we plan to extend our image popularity analysis to cache performance analysis. We also plan to utilize our deduplication observations to improve storage efficiency for Docker registry.

VII. Conclusion

In this paper, we carried out the first comprehensive analysis of container images stored in Docker Hub. We presented a methodology to exhaustively crawl and efficiently download Docker Hub images. Using this approach, we analyzed a 47 TB dataset resulting in 1,792,609 layers and 5,278,465,130 files. Based on this dataset, we carried out a detailed study of a variety of storage metrics on both layers, images, and files. Metrics included layer and image sizes, compressibility, deduplication ratio, and popularity. Our findings reveal that there is room for optimizing how images are stored and used. For example, we observed that compression may not always be beneficial for small layers as it can increase pull latencies. Additionally, layers are rarely shared between images which increases storage utilization. Moreover, file-level deduplication can eliminate 96.8% of the files. We plan to investigate such improvements in the future.

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