

Containers and R—the Rockerverse and beyond

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Abstract The Rocker project provides widely-used Docker images for R across different application scenarios. This article surveys downstream projects building upon Rocker. We also look beyond Rocker to other projects connecting containerisation with R. These use cases and the diversity of applications demonstrate the power of Rocker and containerisation for collaboration, effectiveness, scalability, and transparency.

Introduction

The R community keeps growing. This can be seen in the number of new packages on CRAN, which keeps on growing exponentially (Hornik et al., 2019), but also in the numbers of conferences, open educational resources, meetups, unconferences, and companies taking up, as exemplified by the useR! conference series¹, the global growth of the R and R-Ladies user groups², or the foundation and impact of the R Consortium³. All this cements the role of R as the *lingua franca* of statistics, data visualisation, and computational research. Coinciding with the rise of R was the advent of Docker as a general tool for distribution and deployment of server applications. Combining both these topics, the Rocker Project (<https://www.rocker-project.org/>) provides images with R (see the next Section for more details). The considerable uptake and continued evolution of the Rocker Project has led to numerous projects extending or building upon Rocker images, ranging from reproducible research to production deployments. This article presents this *Rockerverse* of projects across all development stages: early demonstrations, working prototypes, and mature products. We also introduce related activities connecting the R language and environment with other containerisation solutions. The main contribution is a coherent picture of the current lay of the land of using containers in, with, and for R.

The article continues with a brief introduction of containerization basics and the Rocker Project, followed by descriptions of projects developing images with R installations. Then, we present applications, starting with the R packages specifically for interacting with Docker, second-level packages using containers mediately or only for specific features, up to complex use cases leveraging containers. We conclude with a reflection on the landscape of packages and applications and point out future directions of development.

¹<https://www.r-project.org/conferences/>

²<https://www.r-consortium.org/blog/2019/09/09/r-community-explorer-r-user-groups>, <https://www.r-consortium.org/blog/2019/08/12/r-community-explorer>

³<https://www.r-consortium.org/news/announcements>, <https://www.r-consortium.org/blog/2019/11/14/data-driven-tracking-and-discovery-of-r-consortium-activities>



Figure 1: Rockerverse hex sticker

Containerization and Rocker

Docker, an application and service provided by the eponymous company, has in just a few short years risen to prominence for development, testing, deployment and distribution of computer software (cf. Datadog, 2018; Muñoz, 2019). While there are related approaches such as LXC⁴ or Singularity (Kurtzer et al., 2017), Docker has become synonymous with “containerization”—the method of taking software artefacts and bundling them in such a way that use becomes standardized and portable across operating systems. In doing so, Docker had recognised and validated the importance of one very important thread that had been emerging, namely virtualization. By allowing (one or possibly) multiple applications or services to run concurrently on one host machine without any fear of interference between them, an important scalability opportunity is being provided. But Docker improved this compartmentalization by accessing the host system—generally Linux—through a much thinner and smaller shim than a full operating system emulation or virtualization. This containerization is also called operating-system-level virtualization⁵. Typically a container runs one process, whereas virtualization may run whole operating systems at a larger footprint. This makes for more efficient use of system resources (Felter et al., 2015) and allowed another order of magnitude in terms of scalability of deployment (cf. Datadog, 2018). While Docker makes use of Linux kernel features, its importance was large enough so that some required aspects of running Docker have been added to other operating systems to support Docker more efficiently too (Microsoft, 2019b). The success even led to standardisation and industry collaboration (OCI, 2019).

The key accomplishment of Docker as an “application” is to make a “bundled” aggregation of software (the so-called “image”) available to any system equipped to run Docker, without requiring much else from the host besides the actual Docker application installation. This is a rather attractive proposition and Docker’s very easy to use user interface has led to widespread adoption and use of Docker in a variety of domains, e.g., cloud computing infrastructure (Bernstein, 2014), data science (Boettiger, 2015), and edge computing (Alam et al., 2018) [more examples!]. It proved to be a natural match for “cloud deployment” which runs, or at least appears to run, “seamlessly” without much explicit reference to the underlying machine, architecture or operating system: containers are portable and can be deployed with very little in terms of dependencies on the host system—only the container runtime is required. Images are normally built from plain text documents called Dockerfile. A Dockerfile has a specific set of instructions to create and document a well-defined environment, i.e., install specific software and expose specific ports.

For statistical computing and analysis centered around R, the Rocker Project has provided a variety of Docker containers since its start in 2014 (Boettiger and Eddelbuettel, 2017). The Rocker Project provides several lines of containers spanning to from building blocks with R-release or R-devel, via containers with RStudio-Server and Shiny-Server, to domain-specific containers such as *geospatial*. These containers form *image stacks*, building on top of each other for better maintainability and also of note is a series of “versioned” containers which match the R release they contain with the *then-current* set of packages via the MRAN Snapshot views of CRAN (Microsoft, 2019a). The Rocker Project’s impact and importance was acknowledged by the Chan Zuckerberg Initiative’s *Essential Open Source Software for Science*, who provide funding for the project’s sustainable maintenance, community growth, and targeting new hardware platforms including GPUs (Chan Zuckerberg Initiative et al., 2019).

Docker is not the only containerisation software. An alternative stemming from the domain of high-performance computing is **Singularity** (Kurtzer et al., 2017). Singularity can run Docker images, and in the case of Rocker works out of the box if the main process is R, e.g., in *rocker/r-base*, but does not succeed in running images where there is an init script, e.g., in containers that by default run RStudio. In the latter case, a Singularity file, a recipe akin to a Dockerfile, needs to be used. To date, no comparable image stack to Rocker exists on **Singularity Hub**. A further tool for running containers is **podman**, which also can build Dockerfiles and run Docker images. Proof of concepts for using podman to build and run Rocker containers exist⁵. Yet the prevalence of Docker, especially in the broader user community beyond experts or niche systems, and the vast amount of blog posts and courses for Docker, currently caps specific development efforts for both Singularity and podman in the R community. This might quickly change when usability and spread increase, or security features such as rootless/unprivileged containers, which both these tools support out of the box, become more sought after.

⁴<https://en.wikipedia.org/wiki/LXC>

⁵See <https://github.com/nuest/rodman> and <https://github.com/rocker-org/rocker-versioned/issues/187>

Container images

Images for alternative R distributions

As outlined above, R is a widely-used language with a large community. The large number of extension packages provides access to an unrivaled variety of established and upcoming features. Nevertheless, special use cases and experimental projects exist to test approaches or provide features different to what “base R” provides. These projects stem both from academia and industry. *Base R*, sometimes called GNU-R, is the R distribution maintained by the [R Core Team](#) and provided via [CRAN](#).

Microsoft R Open (MRO) is an R distribution formerly known as Revolution R Open (RRO) before Revolution Analytics was acquired by Microsoft. MRO is compatible with main R and its packages. “It includes additional capabilities for improved performance, reproducibility, and platform support.” (Microsoft, a) Most notably these capabilities are the MRAN repository, which is enabled by default, and the (optional) integration with [Intel® Math Kernel Library \(MKL\)](#) for multi-threading in linear algebra operations (Microsoft, b). MRO does not provide official Docker images, but a set of community-maintained Dockerfiles and Docker images `nuest/mro` are available on Docker Hub at <https://github.com/nuest/mro-docker> and on GitHub at <https://github.com/nuest/mro-docker> respectively. The images are inspired by the Rocker images and can be used much in the same fashion, effectively a drop-in replacement allowing users to quickly evaluate if the benefits of MRO + Intel® MKL apply to their use case. Version-tagged images are provided for the latest bugfix release of recent R versions. Extended license information about MKL is printed at every startup.

Renjin is an interpreter for the R language running on top of the [Java Virtual Machine \(JVM\)](#) providing full two-way access between Java and R code (Wikipedia, 2018). It was developed to combine the benefits of R, such scripting and extension packages, with the JVM’s advantages in the areas of security, cross-platform availability, and established position in enterprise settings. R extension packages need to be specially compiled and are distributed via the Java package manager [Apache Maven](#), cf. <http://packages.renjin.org/packages> for available packages. Packages are loaded on demand, i.e., at the first call to `library()`. Not all R packages, especially one linking to binary libraries, are available, e.g., `rgdal`⁶. There are no official Docker images for Renjin, but community-maintained images for selected releases only are available under `nuest/renjin` on Docker Hub and GitHub at <https://hub.docker.com/r/nuest/renjin> and <https://github.com/nuest/renjin-docker> respectively. These images expose the command line interface of Renjin in a similar fashion as Rocker images and allow an easy evaluation of Renjin’s suitability, but are not intended for production use.

pqr is a “a pretty quick version of R”. *pqr* attempts to improve R on some opinionated issues in the R language and is the basis for experimental features, e.g., automatic differentiation⁷. The source code development on GitHub is a one man project and it does not provide any Docker images. But especially disruptive approaches may contribute to the development of the R ecosystem, so the `nuest/pqr` images on Docker Hub and GitHub at <https://hub.docker.com/r/nuest/pqr/> and <https://github.com/nuest/pqr-docker> respectively.

FastR is “A high-performance implementation of the R programming language, built on GraalVM” (<https://github.com/oracle/fastr>). It is developed by Oracle, connects R to the GraalVM ecosystem (wik, 2019), and also claims superior performance but also targets full compatibility with base R⁸. There are no official Docker images provided, but `nuest/fastr` images and Dockerfile are independently maintained on [Docker Hub](#) and [GitHub](#) respectively.

While the images presented in this section are far from being as vetted, stable, and widely used as any of the Rocker images, they demonstrate an important advantage of containerisation technology, namely the ability to transparently build portable stacks of open source software and make them easily accessible to users. All different distributions are published under GPL licenses. Since all of the different R distributions claim better performance as a core motivation, a comparison based on Docker images, potentially leveraging the [resource restriction mechanisms](#) of Docker to level the playing field, seems useful future work.

Bioconductor

Bioconductor (<https://bioconductor.org/>) is an open source, open development project for the analysis and comprehension of genomic data (Gentleman et al., 2004). The project consists of 1741 R software packages as of August 15th 2019, as well as packages containing annotation or experiment data. `_Bioconductor_` has a semiannual release cycle, each release is associated with a particular

⁶<http://packages.renjin.org/package/org.renjin.cran/rgdal/1.4-4/build/1>

⁷<https://riotworkshop.github.io/abstracts/riot-2019-pqr.txt>

⁸<https://github.com/oracle/fastr>

version of R. Docker images allow availability of current and past versions of *Bioconductor* for convenience and reproducibility. *Bioconductor* ‘base’ docker images are built on top of rocker/r-ver and rocker/rstudio. *Bioconductor* installs packages based on the R version, and therefore uses rocker/rstudio and rocker/r-ver version tagging. *Bioconductor* selects the desired version of R from Rocker, adds the BiocManager CRAN package for installing appropriate versions of *Bioconductor* packages, and creates a *Bioconductor* docker image with an informative tag (R_version_Bioc_version). The images are summarized on the *Bioconductor* web site (<https://bioconductor.org/help/docker/>), maintained on GitHub (https://github.com/Bioconductor/bioc_docker), and available to the community through DockerHub. Past and current combinations of R and *Bioconductor* are therefore accessible via a specific docker tag.

Bioconductor has several images in addition to ‘base’, specific to various areas of research. The ‘core’ image installs the most commonly used *Bioconductor* packages. *Bioconductor* images for proteomics, metabolomics, and flow cytometry are community maintained. All community maintained images build on top of the *Bioconductor* base image and therefore indirectly the Rocker images. To simplify building and maintaining *Bioconductor* images, we use a Ruby templating engine. A recent audit of the *Bioconductor* Dockerfiles, following best practices from the Docker website, led to a reduction in the size and number of layers. The most important insights involve the ‘union’ file system used by Docker. In this file system, once a layer (e.g., RUN statement) writes to a file path, the file path is never altered. A subsequent layer that might appear to remove or overwrite the path actually masks, rather than alters, the original. It is therefore important to clean up (e.g., cache removal) within each layer, and to avoid re-installing existing dependencies.

A recent innovation is to produce a *bioconductor_full* image to emulate the *Bioconductor* nightly Linux build machine. The image contains the *system dependencies* needed to install and check almost all (1730 of 1741) *Bioconductor* software packages. Users no longer have to manage complicated system dependencies. The image is configured so that `.libPaths()` has `/usr/local/lib/R/host-site-library` as the first location. Users mounting a location on the host file system to this location then persist installed packages across docker sessions or updates. Many R users pursue flexible work flows tailored to particular analysis needs, rather than standardized work flows. The *bioconductor_full* image is well-suited to this pattern. *bioconductor_full* provides developers with a test environment like *Bioconductor*’s build system.

Use of images suggests several interesting possibilities for the *Bioconductor* project. Images may be valuable in teaching, where participants pull pre-built images to avoid complicated configuration of their own computing environments. An appeal of this over our current approach (providing Amazon Machine Instances for the duration of the course) is the utility of the image to participant after the course is over. *bioconductor_full* introduces a common system configuration, so it becomes increasingly sensible for *Bioconductor* to distribute convenient *binary* packages. Images also suggest approaches to more advanced computational models. For instance, we are exploring use of images for Helm-orchestrated Kubernetes clusters on the Google Cloud Platform. The user interacts with a manager image based on *bioconductor_full*, configured to perform map-reduce style computations via the BiocParallel package communicating with minimally-configured worker images. A strength of this approach is that the responsibility for complex software configuration (including customized development) is shifted from the user to the experienced *Bioconductor* core team.

Images for (historic) R versions

As with any other software, each new version of R comes with its share of changes. Some are breaking changes, some are not, but the fact is that running a piece of code in a given version might give different results from another version can be an issue when it comes to reproducibility of workflows and stability of applications. For example, think about R random seed: starting with R 3.6.0, running `set.seed(2811); sample(1:1000, 2)` will not give the same result as if it was run inside an older version of R. That might seem trivial, but all the code using the random number generator will not be exactly reproducible after this breaking change. Therefore, controlling the version of software is most crucial for reproducible research (e.g. Boettiger, 2015).

Containers are perfectly suited to capture a specific configuration of a computing environment to prohibit such problems. The Rocker images provides the *versioned stack* for different the version of R since the project inception, which use the *then-current* stable Debian base image (cf. Boettiger and Eddelbuettel, 2017). Based on custom build phase hooks⁹, i.e., small shell scripts executed at different phases in the automated build of Rocker images, there are also semantic version tags for the most recent frozen (i.e., using MRAN) versions with only the major and minor version¹⁰. So, at the time of

⁹<https://docs.docker.com/docker-hub/builds/advanced/>

¹⁰See <https://github.com/rocker-org/rocker-versioned/blob/master/VERSIONS.md>, FIXME:
<https://github.com/rocker-org/rocker-versioned/issues/42>.

writing this article, `rocker/r-ver:3` and `3.6` are aliases for `3.6.0`, because `3.6.1` is the latest release. With the release of `3.6.2` and pinning of the MRAN version in `3.6.1`, the tags `3` and `3.6` will deliver the same image as `3.6.1`. These tags allow users to update the base image to retrieve bugfixes while reducing the risk of also introducing breaking changes.

`r-online` is an app for helping users to detect breaking changes between different R versions, and for historic exploration of R. With a standalone NodeJS app or `online`, the user can compare a piece of code run in two separate versions of R. Internally, `r-online` opens one or two Docker instances with the given version of R based on Rocker images, executes a given piece of code, and returns the result to the user.

A container also provides an isolated sandbox environment suitable for testing and evaluation, without interfering with the “main” working environment. This enables cross version testing and bugfixing. To take this even further, the Rocker contributors are discussing the provision of R versions reaching back further than the project’s own inception, reaching back as far as R 2.x and 1.x¹¹. The main challenges are finding a suitable base image with a matching OS version, or making the adjustments to compile R on more recent OS releases.

Windows Images

Docker containers on the Windows operating system were originally quite cumbersome to use. They required an extra tool, `Docker Toolbox`, which by now only exists as a legacy solution for older Windows systems. Docker toolbox leverages `docker-machine` (see also Section [Interfaces for Docker in R](#) for an R package interfacing with `docker-machine`) to handle the process of creating a local virtual host which could host Docker Engine, while exposing the regular Docker CLI. The Docker CLI commands are forwarded to the virtual host transparently for the user. For current Windows Server (2016 and later) and Windows Desktop (`Docker Desktop` requires Windows 10) versions, Docker is supported natively¹² and different base images are offered by Microsoft¹³. The Docker CLI can be used in just the same way as on other operating systems but not every base image is supported on every Windows host¹⁴. On Docker Desktop for Windows, the user can run both Linux-based and Windows-based containers, but only one of the Docker daemons can be used at a time¹⁵.

`rocker-win` (<https://github.com/nuest/rocker-win>) is a proof of concept for running R in Windows-based containers (Nüst, 2019). It provides selected R versions using three different base images using `microsoft/windowsservercore` and `mcr.microsoft.com/windows/servercore`. These base images match different Windows versions: Windows Server 2019, Windows Server 2016, and Windows Server, version 1803. The images are built using two CI services, `Travis CI` and `Appveyor`, which provide the different Windows versions and therefore support different base images, and published automatically on `Docker Hub`. The images are built from manually maintained separate Dockerfiles, are tagged with both Windows-variant and R version, e.g., `nuest/rocker-win:1tsc2019-3.6.2` or `nuest/rocker-win:1803-latest`, and run the `R.exe` process by default. New R versions are only added on demand. The explorative project demonstrates the variety and potentially confusing complexity of Windows on Docker, e.g., because of the different base images, but also provides a starting point for any Windows-constrained user to leverage containerisation, including examples for apps using `\pkg{plumber}`, `Shiny`, or R packages with system dependencies such as `sf`. The latter is quite comfortable actually, as R ships pre-compiled binaries for Windows.

For Windows, just as originally for Linux, the cloud use cases drive the development and Docker and Microsoft collaborate closely¹⁶. In most cases, individual developers or researchers worrying about reproducibility, will prefer the more widely and host independent Linux-based containers. Naturally, a Windows license is required for the host machine. But the developments in the `rocker-win` prototype show that containers can also be used for R workflows depending on Windows-only tools, for leveraging an existing Windows Server-based infrastructure where policies can otherwise not be met, or for streamlining interactions with system operating staff that runs Windows-based containers themselves.

¹¹<https://github.com/rocker-org/rocker-versioned/issues/138>

¹²<https://www.docker.com/products/windows-containers>

¹³<https://docs.microsoft.com/en-us/virtualization/windowscontainers/about/index>

¹⁴<https://docs.microsoft.com/en-us/virtualization/windowscontainers/deploy-containers/version-compatibility>

¹⁵See “Switch between Windows and Linux containers” on <https://docs.docker.com/docker-for-windows/>.

¹⁶<https://www.docker.com/partners/microsoft>

Non-Debian Linux images

The **R-hub** project provides “a collection of services to help R package development”, with the package builder as the most prominent one (R-hub project, 2019). The builder allows R package developers to check their R package on different platforms and R versions using a web form or the package **rhub** (Csárdi and Salmon, 2019). The builder uses Docker containers to conduct these checks, taking advantages of their well-defined environments and sandboxing. The Dockerfiles and images are published on Docker Hub¹⁷ and GitHub¹⁸ respectively. The images comprise release and development builds of R running in the base images of the **Debian**, **Ubuntu**, **Fedora**, and **CentOS** linux distributions (Arch Linux is under development¹⁹, see `rhub::local_check_linux_images()` for a full list), and are intended for debugging (see Section **Development and debugging**) not for reproducible workflows. The rationale of not re-using the Rocker image stack is the high number of operating systems and configurations, which can be more uniformly maintained in a separate suite of images. Also, a common structure across the respective image stacks of the operating systems, e.g., for **debian**, adding **GCC** in **debian-gcc** and then R’s development version in **debian-gcc-devel**. The platform also has a specific user configuration differing from the setup covering typical applications of Rocker images, and the images include considerably more software, such as a fairly complete **LaTeX** installation, to provide an experience closer to CRAN.

RStudio also maintains a set of **Docker images** for multiple operating systems including **SUSE**, **Ubuntu**, **CentOS**, and **Debian**. The image stacks include an **opinionated R installation** and ensure the R installation and profile is consistent across the different Linux distributions. The images also install R in a versioned directory and use a minimal set of build and runtime dependencies. Furthermore these images are responsible for creating pre-compiled binary R packages for Linux, which supplement the binaries built by CRAN. These pre-compiled packages dramatically decrease the installation time of R packages on Linux and subsequently can decrease the build time of Docker images (Lopp, 2019).

There are also independent projects installing R or RStudio on **Alpine Linux**, but not beyond the proof of concept stage²⁰. In general, Alpine-based Docker images are often chosen for minimalistic and thereby small and secure containers, e.g., in hardware with limited storage. R-hub’s proof of concept **r-minimal** takes this to the extreme with compressed image size of 20MB and bespoke install scripts, e.g., to cleverly remove compilers after package installation. For R though, this advantage quickly deteriorates if more features are needed, e.g. if adding compilers, packages, or especially if installing powerful data science and communication tools, like RStudio or LaTeX. Furthermore the distribution uses the **musl C library** instead of the **glibc** used in **Debian/Ubuntu**, for which more tooling and experiences exist²¹. In fact, using **Debian**’s ‘**slim**’ variant and removing capabilities, one could probably achieve similarly small image sizes on a more common stack.

altRnative (<https://github.com/ismailsunni/altRnative/>) is an experimental R package for running the same code across multiple containerised versions of R, intended for comparison across operating systems and different implementations of R. It comes with a collection of Dockerfiles and corresponding images in multiple combinations, currently including, e.g., **MRO**, **FastR**, **Fedora**, and **TERR**²².

Data Science images

Data Science is a widely discussed topic among all academic disciplines (cf. e.g., Donoho, 2017). Using computers and complex software to make sense of (large amounts of) collected or simulated data is a cross-cutting phenomenon leading to **X Data Science** disciplines, seminars, and study majors. The practice to apply a combination tools and software stacks for analysing data and the cross-cutting skillsets connected with data science puts the management of computing environments and the challenges of reproducibility high up on the agenda. This awareness leads to a large number of bespoke Docker images but also some commonly used image stacks, ranging from base images with very common tools to ‘catch all’ images including a lot of software. Here we only mention a few image stacks as examples, which are not based on Rocker images or stem from the R community, but prominently include installations of R. A general description of what to consider when creating a

¹⁷<https://hub.docker.com/u/rhub>

¹⁸<https://github.com/r-hub/rhub-linux-builders>

¹⁹<https://github.com/r-hub/rhub-linux-builders/pull/41>

²⁰<https://gitlab.com/artemklevtsov/r-alpine> or <https://www.github.com/velaco/alpine-r> provide different use case images but are not recently maintained (development of the latter documented in Ratesic (2018)); <https://github.com/cmplopes/alpine-r> has only base R images, is relatively up-to-date but sparsely documented; <https://github.com/CenterForStatistics-UGent/mountainr> is a ghost project with only a single short ‘Dockerfile’, yet it shows the easy installation of the latest R from Alpine sources

²¹Cf. <https://github.com/rocker-org/rocker/issues/231>

²²See ‘Dockerfile’s at <https://github.com/ismailsunni/dockers>.

Docker image used for data science projects in R is provided on environments.rstudio.com.

The **Jupyter Docker Stacks** project are a set of ready-to-run Docker images containing Jupyter applications and interactive computing tools (Jupyter, 2018). The `jupyter/r-notebook` image includes R and “popular packages”, and R is also included in the `catchall/datascience-notebook` image²³. For example, these images allow users to quickly start a Jupyter Notebook server locally or build their own specialised images on top of stable toolsets.

Kaggle provides the `gcr.io/kaggle-images/rstats` image (previously `kaggle/rstats`) and corresponding Dockerfile for usage in their Machine Learning competitions and easy access to the associated datasets. It includes machine learning libraries such as Tensorflow and Keras, and also configures the **reticulate** package. The image uses a base image with *all packages from CRAN*, `gcr.io/kaggle-images/rcran`, which requires a Google Cloud Build as Docker Hub would time out²⁴. The final extracted image size is over 25GB, which makes it debatable if having everything available is actually convenient.

As a further example, **Radiant** project provides several images, e.g., `vnijs/rsm-msba-spark`, for their browser-based business analytics interface based on **Shiny** (Dockerfile on GitHub) and for use in education as part of an MSc course. As data science often applies a multitude of tools, this image favours inclusion over selection and features Python, Postgres, JupyterLab and Visual Studio Code besides R and RStudio, bringing the image size up to 9GB.

Use cases and applications

Interfaces for Docker in R

Interfacing with the Docker daemon is typically done through the **Docker Command Line Interface** (Docker CLI). However, moving back and forth between an R console and the command line can create friction in workflows and reduce reproducibility. A number of first-order R packages provide an interface to the Docker CLI, allowing to automate interaction with the Docker CLI from an R console.

Each of these packages has particular advantages as they provide function wrappers for interacting with the Docker CLI at different stages of a container’s life cycle. Examples of such interactions are installing the Docker software, creating Dockerfiles (**dockerfiler**, **containerit**), building images and launching a containers (**stevedore**, **docker**) on a local machine or on the cloud. As such, the choice of which package is most useful depends on the use-case at hand, but also the users level of expertise.

Functionality	AzureContainers	babelwhale	dockermachine	dockyard	harbor	stevedore
Generate a Dockerfile				✓		
Build an image	✓			✓		
Execute a container locally or remotely	✓	✓	✓	✓	✓	✓
Deploy or manage an instances in the cloud	✓		✓		✓	✓
Interact with an instance (e.g. file transfer)		✓	✓			✓
Manage storage of images					✓	✓
Supports Docker and Singularity		✓				
Direct access to Docker API instead of using the CLI						✓
Installing Docker software			✓			

stevedore (<https://cran.r-project.org/package=stevedore>)

AzureContainers (<https://cran.r-project.org/package=AzureContainers>) is an interface to a number of container-related services in Microsoft’s **Azure Cloud**, namely **Container Instances**, **Container Registry**, and **Kubernetes Service**. While it is mainly intended for working with Azure, as a convenience feature it includes lightweight, cross-platform shells to Docker and Kubernetes (tools `kubect1` and `helm`). These can be used to create and manage arbitrary Docker images and containers, as well as Kubernetes clusters on any platform or cloud service.

babelwhale (<https://cran.r-project.org/package=babelwhale>) allows executing and interact-

²³<https://jupyter-docker-stacks.readthedocs.io/en/latest/using/selecting.html>

²⁴Originally, a stacked collection of over 20 images with automated builds on Docker Hub was used, see <https://web.archive.org/web/20190606043353/http://blog.kaggle.com/2016/02/05/how-to-get-started-with-data-science-in-containers/> and <https://hub.docker.com/r/kaggle/rcran/dockerfile>

ing with containers, which can use either Docker or Singularity as a backend. The package provides a unified interface to interact with Docker and Singularity containers. Users can, for example, execute a command inside a container, mount a volume or copy a file.

harbor (<https://github.com/wch/harbor>)

dockyard (<https://github.com/thebioengineer/dockyard>) has the goal of lowering barrier to creating Dockerfiles and Docker images, and deploying Docker containers. The way docker images are made is by reading and following a set of instructions found in Dockerfiles. This requires stepping out of the R ecosystem and into an infrastructure mindset where the user needs to specify the environment they require. Because Dockerfiles can be read as a series of steps, this lends itself well to the tidyverse style of programming where each step is piped into the next. dockyard has a Dockerfile object that either starts out as an empty Dockerfile, or can use existing Dockerfile to use as a template. This combined with a series of functions that are analogous to the steps commonly found in a Dockerfile, it makes building Docker images much more approachable to R users. There are also wrappers for commonly used steps for R programmers like adding libraries and copying files into the R Docker containers. Once the Dockerfile is created, dockyard has built-in functionality to build the image and run a container.

dockermachine (<https://github.com/cboettig/dockermachine>) is an R package to provide a convenient interface to Docker Machine from R. Docker Machine's CLI tool docker-machine allows users to create and manage virtual host on local computers, local data centers, or at cloud providers. A local Docker installation can be configured to forward all commands issues on the local Docker CLI to a selected (remote) virtual host fully transparent. For local Docker Machine was especially crucial in early days of Docker, when no native Docker support was available for Mac or Windows computers, but remains relevant for provisioning on remote systems. The package has not received any updates for two years, but was functional with a current version of docker-machine (0.16.2) and potentially lowers the barriers for R users to run containers on various hosts, if using the Docker Machine CLI is perceived as a barrier.

Capture and create environments (?)

Several second order R packages attempt to make the process of creating Docker images and using containers for specific tasks, such as running tests or rendering reproducible reports, easier.

- [dockerfiler](#)
- [containerit](#)
- [dockr](#), see also <http://smaakage85.netlify.com/2019/12/21/dockr-easy-containerization-for-r/>
- [dockertest](#)
- [renv with Docker](#)
- <https://github.com/gigantum/base-images>

liftr (<https://nanx.me/liftr/>) (Xiao, 2019) aims to solve the problem of persistent reproducible reporting in statistical computing. Currently, the R Markdown format and its backend compilation engine *knitr* offer a *de facto* standard for creating dynamic documents (Xie et al., 2018). However, the reproducibility of such content authoring environments is often limited to individual machines — it is not easy to replicate the system environment (libraries, R versions, R packages) where the document was compiled. This issue becomes even more serious when it comes to collaborative document authoring and creating large-scale document building services. *liftr* solves this reproducibility problem by bringing Docker to the game. In essence, *liftr* helps R Markdown users create and manage Docker containers for rendering the documents, thus make the computations utterly reproducible across machines and systems.

On implementation, with no side effects, *liftr* extended and introduced new metadata fields to R Markdown, allowing users to declare the dependencies for rendering the document. *liftr* parses such fields and generates a Dockerfile for creating Docker containers. *liftr* then helps render the document inside the created Docker container. This workflow is summarized in Figure 2.

knitr and R Markdown are used as the template engine to generate the Dockerfile. Features such as caching container layers for saving image build time, automatic housekeeping for fault-tolerant builds, and Docker status check are supported by *liftr*. Four RStudio addins are also offered by *liftr* to allow push-button compilation of documents and provide better IDE integrations.

Three basic principles are followed to design the *liftr* package since its inception.

1. Continuous reproducibility. Continuous integration, continuous delivery, and continuous deployment are well-accepted practices in software engineering. Similarly, it is believed by the authors of *liftr* that ensuring computational reproducibility means a continuous process instead

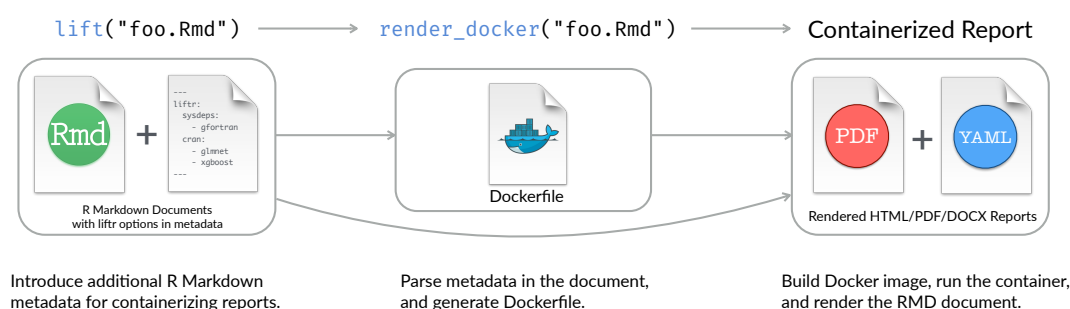


Figure 2: The liftr workflow for rendering containerized R Markdown documents.

of creating static data/code archives or a one-time deal. Specifically, the software packages used in data analysis should be upgraded regularly in a manageable way. Therefore, *liftr* supports specifying particular versions of package dependencies, while users are encouraged to always use the latest version of packages (without a version number) by default.

2. Document first. Many data analysis workflows could be wrapped as either R packages or dynamic documents. In *liftr*, the endpoint of dynamic report creation is the focus of containerization, because this offers more possibilities for organizing both computations and documentation. Users are encouraged to start thinking from the visible research output from the first day.
3. Minimal footprint. R Markdown and Docker are already complex software systems. Making them work together seamlessly can be complicated. Therefore, API designs such as function arguments are simplified while being kept as expressive and flexible as possible.

In summary, *liftr* tries to redefine the meaning of computational reproducibility by offering system-level reproducibility for data analysis. It provided a practical way for achieving it — a new perspective on how reproducible research could be done in reality. Further, sharing system environments for data analysis also becomes extremely easy, since users only need to share the R Markdown document (with a few extra metadata fields), and compile them with *liftr*. As an example, *liftr* demonstrated its advantage for R Markdown-based computational workflow orchestration, by effortlessly containerizing 18 complex *Bioconductor* workflows in the DockFlow project (<https://dockflow.org>) in 2017.

One of the key tool of Docker are Dockerfiles, which can be thought of as “recipes” used to build a specific image. But building these files can feel like a workflow break as it demands to open a separate file, and / or to write a small wrapper around R’s `write()` function to add elements to the file. At the same time, doing it by hand prevents from using programming language for what they are good for: iteration, and automation. Iteration and automation for Dockerfiles is the very reason behind *dockerfiler*, an R package designed for building Dockerfiles straight from R.

For example, the *golem* package makes an heavy use of *dockerfiler* when it comes to creating the Dockerfile for building production-grade Shiny applications and deploying them. The reason behind this is that *dockerfiler*, on top of being scriptable from R, can leverage all the tools available in R to parse a DESCRIPTION file, to get system requirements, to list dependencies, versions, etc.

Deployment to cloud services

The cloud is the natural environment of containers, and becomes the go-to mechanism to expose applications written in R to users.

- *RSelenium*
- *googleComputeEngineR* (function `gce_vm_template()`)
 - To enable quick deployments of key R services such as RStudio and Shiny onto cloud virtual machines (VMs), this package utilises Dockerfiles to move the labour of setting up those services from the user to a premade Docker image. For example, by specifying the template `template="rstudio"` in `gce_vm_template()/gce_vm()` an up to date RStudio Service image is launched. Specifying `template="rstudio-gpu"` will launch an RStudio Server image with a GPU attached, etc.
- *analogsea* (digital ocean R client)
- *plumber*
- production deployment of neural networks (?, ?)

- Kubernetes - A popular platform for managing Docker containers is [Kubernetes](#), which is used for a wide variety of containerized applications. It may be your organisation has a Kubernetes cluster already for other applications. Docker containers are used within Kubernetes clusters to hold native code, for which Kubernetes creates a framework around network connections and scaling of resources up and down. An introduction on using [Kubernetes with R](#) is published at [this blog post](#).
- [AzureContainers](#): Umbrella package for working with containers in Microsoft's Azure cloud. Provides interfaces to three Azure services: Container Registry, Container Instances (for running individual containers), and Kubernetes Services (for orchestrated deployments)

Using R to power enterprise software in production environments

R has been historically viewed as a tool for analysis and scientific research—not for creating software that corporations can rely on to continuously run in real time. However, thanks to advancements in R running as a web service, along with the ability to deploy R in Docker containers, modern enterprises are now capable of having real-time machine learning powered by R.

The backbone of this work is the **plumber** (<https://www.rplumber.io/>) package. The plumber package allows R to be used to host web services through RESTful APIs. When R is running on a server, a different server can ask R to make a computation through an HTTP request and get an immediate response. For instance, if a data scientist at a company creates a machine learning model to tell which customers are likely to make a repeat purchase, if they serve the model through a plumber API then someone else on the marketing team could write software that sends different emails depending on that real-time prediction. Plumber syntax is simple to read and understand: the API is created by commenting above function names in an R script.

```
## Return the sum of two numbers
## @get /random
function(){
  runif()
}
```

Example of a plumber API to generated a random number by visiting <http://127.0.0.1/random>

Plumber becomes far more powerful with the addition of Docker. Docker can be used to create images that [include both R and plumber](#). Then when the image is deployed, that creates the web endpoints that other services can hit and call the R code. This pattern of deploying code mimics those used by software engineering services created in Java, Python, and other modern languages. By using Docker to deploy plumber APIs, R can be used alongside those languages as a first class member of a software engineering technical stack.

At T-Mobile, R is used to power real-time services that are called over a million times a day. T-Mobile created a set of neural network machine learning natural language processing models to help customer care agents manage text-based messages for customers ([T-Mobile et al., 2018](#)). The models are convolutional neural networks that use the RStudio Keras package and are built on top of a Rocker Docker image. Since the models power tools for agents and customers, they need to have extremely high uptime and reliability—and they found that R is able to perform. The AI @ T-Mobile team open sourced their Docker images [on GitHub](#).

Deployment to the cloud

While Plumber provides the low-level infrastructure for turning a statistical model into a predictive service, for production purposes it is usually necessary to take into account considerations such as scalability, reliability and ease of management. A single container is limited in the volume of requests it can service. Furthermore, if the container goes down, or is occupied with processing a computationally intensive task, the service becomes unavailable until it is restarted.

These issues can be mitigated by deploying not a single container, but a *cluster* of containers, orchestrated as a single deployment. The deployment system of choice at the time of writing is [Kubernetes](#). This allows you to deploy a single image to a pool of servers, which can then serve requests in parallel. Client-side requests are made to the cluster ingress endpoint, which then redirects them to individual servers. The orchestrator can identify cluster nodes that have failed, and restart them automatically; it can also detect when there is no capacity to service more requests, and start additional servers and containers as needed.

While these load-balancing and autoscaling properties of a Kubernetes cluster are invaluable, they are still limited by the hardware resources that it has access to. A cluster cannot scale out if it

has run out of servers. This issue in turn can be addressed by deploying not to on-premise servers but to the cloud, where effectively unlimited computing resources are available (as long as one can pay for them). From a management perspective, cloud deployments have the additional advantage that hardware maintenance becomes the responsibility of the cloud provider, eliminating another pain point. Orchestrator services are available from all the major cloud service providers, including Amazon Web Services (AWS), Google Cloud Platform, and Microsoft Azure.

An example of an R package for working with containers in the cloud is AzureContainers, which interacts with three Azure services: Container Instances (for running a single container), Container Registry (a private docker registry service), and Kubernetes Service (for Kubernetes on Azure). AzureContainers provides a lightweight yet powerful interface for working with Resource Manager, the framework for deploying and managing arbitrary resources in Azure. On the client side, it provides simple shells to the Docker, Kubectl and Helm tools that are commonly used for managing containers and Kubernetes clusters.

Here is some simple code that pushes a Docker image to an Azure Container Registry, and then creates a deployment using Azure Kubernetes Service. This is a slightly modified version of the code from the “Deploying a prediction service with Plumber” AzureContainers vignette. The code makes use of a yaml file to define the deployment and predictive service, which is standard practice with Kubernetes; the yaml can be seen in the aforementioned vignette.

```
library(AzureContainers)
# create a resource group for our deployments
deployresgrp <- AzureRMR::get_azure_login()$
  get_subscription("subscription_id")$
  create_resource_group("deployresgrp", location="australiaeast")

### create a container registry
deployreg_svc <- deployresgrp$create_acr("deployreg")

# build our image (a random forest on the Boston housing data, available in the MASS package)
call_docker("build -t bos-rf .")

# upload the image to Azure
deployreg <- deployreg_svc$get_docker_registry()
deployreg$push("bos-rf")

### create a Kubernetes cluster with 2 nodes
deployclus_svc <- deployresgrp$create_aks("deployclus", agent_pools=aks_pools("pool1", 2))

# grant the cluster pull access to the registry
gr <- AzureGraph::get_graph_login()
aks_app_id <- deployclus$properties$servicePrincipalProfile$clientID
reg$add_role_assignment(gr$get_app(aks_app_id), "Acrpull")

# get the cluster endpoint
deployclus <- deployclus_svc$get_cluster()

# create and start the service
deployclus$create("bos-rf.yaml")
```

Once the service has been created, we can check on its status and obtain predictions:

```
deployclus$get("deployment bos-rf")
#> Kubernetes operation: get deployment bos-rf --kubeconfig="../../../kubeconfigxxxx"
#> NAME      DESIRED   CURRENT   UP-TO-DATE   AVAILABLE   AGE
#> bos-rf    1         1         1            1           5m

deployclus$get("service bos-rf-svc")
#> Kubernetes operation: get service bos-rf-svc --kubeconfig="../../../kubeconfigxxxx"
#> NAME      TYPE          CLUSTER-IP   EXTERNAL-IP   PORT(S)          AGE
#> bos-rf-svc LoadBalancer  10.0.8.189   xxx.xxx.xxx.xxx 8000:32276/TCP   5m
```

```
response <- httr::POST("http://xxx.xxx.xxx.xxx:8000/score",
  body=list(df=MASS::Boston[1:10,]), encode="json")
httr::content(response, simplifyVector=TRUE)
#> [1] 25.9269 22.0636 34.1876 33.7737 34.8081 27.6394 21.8007 22.3577 16.7812 18.9785
```

Note that Plumber, by itself, provides no authentication or security features; anybody who knows the cluster's IP address can access the predictive service. At minimum, a basic authentication layer should be added to any Kubernetes deployment. Standard Kubernetes procedure involves creating an ingress controller, for example with the nginx or traefik reverse proxy software, and one can then add application-specific authentication layers on top of that (for example, to authenticate with a user's Azure Active Directory or LDAP credentials). More details can be found from most Kubernetes learning resources, and are outside the scope of this paper.

Continuous integration and continuous delivery (?, ?)

The controlled nature of containers, i.e., it is possible to define the software environment very well, even on remote machines, make them also useful for continuous integration (CI) and continuous delivery of applications.

- DevOps
 - <https://www.opencpu.org/posts/opencpu-with-docker/>

When doing continuous integration and continuous delivery, it's crucial to test in an environment that matches the production environment. Tools like GitLab-CI are built on top of Docker images: the user specifies a base Docker image, and the whole tests are run inside this environment. But, as we just said, this environment has to be fixed, but it also have to contain the necessary toolkit. In order to achieve that, `r-ci` combines rocker versioning and a series of tools specifically designed for testing. That way, package builders can use this image as a base image for there testing environment, without having to install the necessary packages every time they need to run a new test.

- `dynwrap` (?)
 - For this project, we use travis-ci to build rocker-derived containers, test them, and only push them to docker hub (from travis-ci.org) if the integration tests succeed.
- Google Cloud Build
 - <https://cloud.google.com/cloud-build/>
 - Cloud Build is another continuous intergation service that helps move the workload of building the Docker images to an online service. Cloud Build can be set up to build the Dockerfiles on each GitHub commit or release. This means you do not need to build the Docker images locally, which can tie up resources since Docker images can be several GBs and take a long time to compile. Google Cloud Build works alongside Google Container Registry to allow you to build private and public Docker images, which allows you to build up your own dependency graphs for downstream applications.

Common or public work environments

The fact that Docker images are portable and well defined make them useful when more than one person needs access to the same computing environment. This is even more useful when some of the users do not have the expertise to create such an environment themselves, and when these environments can be run in public or shared infrastructure.

holepunch (<https://github.com/karthik/holepunch>) is an R package that was designed to make sharing work environments accessible to novice R users based on **Binder**. The [Binder project](#), maintained by the team behind Jupyter, makes it possible for users to create and share their computing environments with others ([Jupyter et al., 2018](#)). A *BinderHub* allows anyone with access to a web browser and an internet connection to launch a temporary instance of these custom environments and execute any workflows contained within. From a reproducibility standpoint, Binder makes it exceedingly easy to compile a paper, visualize data, and run small examples from papers or tutorials without the need for any local installation. To set up Binder for a project, a user typically starts at an instance of a BinderHub and passes the location of a repository with a workspace, e.g., a hosted Git repository, or a data repository like Zenodo. Binder's core internal tool is `repo2docker`. It deterministically builds a Docker image by parsing the contents of a repository, e.g., project dependency configurations or simple configuration files. In the most powerful case, `repo2docker` builds a given Dockerfile. While

this approach works well for most run of the mill Python projects, it is not so seamless for R projects. For any R projects that use the Tidyverse suite (Wickham et al., 2019), the time and resources required to build all dependencies from source can often time out before completion, making it frustrating for the average R user. *holepunch* removes some of these limitations by leveraging Rocker images that contain the Tidyverse along special Jupyter dependencies, and only installs additional packages from CRAN and Bioconductor that are not already part of these images. It shortcuts the configuration file parsing in *repo2docker* and starts with the Binder/Tidyverse base images, which eliminates a large part of the build time and in most cases results in a binder instance launching within a minute. *holepunch* as a side effect also creates a DESCRIPTION file which then turns any project into a research compendium (Marwick et al., 2018). The Dockerfile included with the project can also be used to launch a RStudio server locally, i.e., independent of Binder, which is especially useful when more or special computational resources can be provided there. The local image usage reduces the number of separately managed environments and thereby reduces work and increases portability and reproducibility.

In **high-performance computing**, one use for containers is to run workflows on shared local hardware where teams manage their own high-performance servers. This can follow one of several design patterns: users may deploy containers to hardware as a work environment for a specific project, containers may provide per-user persistent environments, or a single container can act as a common multi-user environment for a server. In all cases, though, the containerized approach provides several advantages: First, users may use the same image and thus work environment on desktop and laptop computers, as well. The former models provide modularity, while the latter approach is most similar to a simple shared server. Second, software updates can be achieved by updating and redeploying the container, rather than tracking local installs on each server. Third, the containerized environment can be quickly deployed to other hardware, cloud or local, if more resources are necessary or in case of server destruction or failure. In any of these cases, users need a method to interact with the containers, be it an IDE, or command-like access and tools such as SSH, which is usually not part of standard container recipes and must be added. The Rocker project provides containers pre-installed with the RStudio IDE. In cases where users store nontrivial amounts of data for their projects, data needs to persist beyond the life of the container. This may be via shared disks, attached network volumes, or in separate storage where it is uploaded between sessions. In the case of shared disks or network-attached volumes, care must be taken to persist user permissions, and of course backups are still necessary. When working with multiple servers, an automation framework such as *Ansible* may be useful for managing users, permissions, and disks along with containers.

Using GPUs (graphical processing units) as a specialised hardware from containerized common work environments is also possible and useful (Haydel et al., 2015). GPUs are increasingly popular for compute-intensive machine learning tasks, e.g., deep artificial neural networks (Schmidhuber, 2015). Though in this case, containers are not completely portable between hardware environments. Containers running GPU software require drivers and libraries specific to GPU models and versions, and containers require a specialized runtime to connect to the underlying GPU hardware. For NVIDIA GPUs, the *NVIDIA Container Toolkit* includes a specialized runtime plugin for Docker and a set of base images with appropriate drivers and libraries. The Rocker project has (beta) images based on these that include GPU-enabled versions of machine-learning R packages: <https://github.com/rocker-org/ml>.

Teaching is a further example where sharing a prepared computing environment can greatly improve the process, especially for courses that require access to a relatively complex setup of software tools, e.g., as in the case of database systems. R is a fantastic tool when it comes to interfacing with databases: almost every open source and proprietary database system has an R package that allows users to connect and interact with it. This flexibility is even broader now that we have tools like *DBI*, that allows to create a common API for interfacing these databases, or like *dbplyr*, which are designed to run *dplyr* code straight against the database. But learning and teaching these tools comes with a cost: the cost of deploying or having access to an environment with the softwares and drivers installed. For people teaching R, it can become a barrier if they need to install local versions of the drivers, or to connect to remote instances which might or might not be made available by IT services. Giving access to a sandbox for the most common database environments is the idea behind *r-db* (?), a Docker image that contains everything needed to connect, from R, to a database. Notably, with *r-db*, the users don't have to install complex drivers or to configure their machine in a specific way. On top of that, *r-db* comes with a comprehensive [online guide](#), explaining how to spin a Docker instance of a specific database, and how to use *r-db* to connect to it. Each package contained inside this image also has a series examples, so that the user can get started with the database right away. The rocker/tidyverse base image ensures that users can also readily use packages for analysis, display, and reporting.

RCloud uses a rocker/drd base image for creation of collaborative data analysis and visualisation environments.

Using Docker in a commercial Data Science Platform

In addition to embedding RStudio Open Source Server inside of Docker images, such as Rocker, RStudio offers the modular data science platform [RStudio Team](#), a commercial product allowing teams of data scientists and their respective IT/DevOps groups to develop and deploy code in R and Python. RStudio team enables these groups to use the benefits of containers, without requiring users to learn new tools or directly interact with containers. Notable patterns include:

1. *To deploy and manage RStudio Professional Products:* Many RStudio customers are managing professional products in Docker containers as an alternative to bare-metals servers or virtual machines. Best practices for [running RStudio with Docker containers](#) as well as [Docker images](#) for RStudio's commercial products are available.
2. *To run interactive RStudio sessions on a cluster:* In the RStudio Server Pro 1.2 release in 2019, RStudio added new functionality called [Launcher](#). It gives users the ability to spawn RStudio instances and background jobs in a scalable way on external clusters, e.g., [Kubernetes based on Docker images](#) or [Slurm](#) clusters, and optionally, with Singularity containers. A key benefit of Launcher is the ability for R and Python users to interactively work in RStudio without learning about Docker at all - while still leveraging containers and Kubernetes. Users can submit batch jobs to Kubernetes clusters without writing specific deployment scripts.

[RStudio Connect](#) is a commercial publishing platform to deploy dashboards, REST APIs, and other R and Python content into production. RStudio Connect uses an approach to isolate deployed R applications that is similar to Docker's filesystem and process namespacing and leverages the [RStudio Package Manager](#) to manage R environments including system dependencies. RStudio Package manager may also be used to [manage their R environments and package versions with Docker](#) and to ensure deterministic image builds.

Processing [div]

The portability of containers becomes particularly useful when complex processing tasks shall be offloaded to a server.

- Docker images for cloud services
 - A popular application of using Docker is to create the environments that can run in parallel for speeding up R code. For example, [googleComputeEngineR's gce_vm_cluster\(\)](#) function can create clusters of 2 or more virtual machines, running multi-CPU architectures. Instead of running a local R script with the local CPU and RAM restrictions, the same code can be processed on all CPU threads of the cluster of machines in the cloud, all running in a Docker container with the same R environments. This is achieved through [googleComputeEngineR's](#) integration with the R parallelisation library [library\(future\)](#) by [Henrik Bengtsson](#). Local R computation can be thrown up to a multi-CPU and VM environment to achieve parallel computation in a few lines of R code in your local session. - [some demonstrations are available here](#).
- [Google Cloud Run](#) - This is a CaaS (Containers as a Service) that lets you launch a Docker container without worrying about underlying infrastructure. This dispenses with the developer creating a cloud server to run the Docker image on, by abstracting away those servers to a more serverless configuration. Cloud Run lets you run your code on top of a managed or your own Kubernetes cluster running Knative, and can accept any Docker image. The service takes care of network ingress, scaling machines up and down to zero, authentication and authorisation, all features which are non-trivial for a developer to create on their own. This can be used to scale up R code to millions of instances if they need to, with little or no changes to existing code. An R implementation is shown here at [cloudRunR](#) which uses Cloud Run to create a scalable R plumber API.
- [batchtools](#) ([Lang et al., 2017](#)) can [schedule jobs with Docker Swarm](#)
- scalable deployments, e.g., start with numerous Shiny talks mentioning Rocker at [useR!2017](#)
- [dynmethods](#) (?): In order to evaluate ± 50 computational methods which all used different environments (R, Python, C++, ...), we wrapped each of them in a docker container and can execute these methods from R. Again, all of these containers are being built on [travis-ci](#), and will only be pushed to docker hub if the integration test succeeds.
- [drake](#), <https://docs.ropensci.org/drake/index.html?q=docker#with-docker>

Research Compendia (?)

- <https://github.com/benmarwick/rrtools>

- `renv`, <https://rstudio.github.io/renv/articles/docker.html>

Development and debugging

Containers can also serve as useful playgrounds to create environments ad-hoc or to provide very specific environments that are not often needed. Developers can readily start a local container based on a Rocker image to investigate a bug report, which might require them to install a specific combination of package versions or use a specific R version (see also versioned images above). Unlike recreating the reporter's environment on their regular machine, a container can simply be discarded after use, and there is no need to tediously roll back explorative changes to a previous state. Using the Rocker images with RStudio, the disposable environments lack no development comfort (see also the usage in research compendia).

`r-debug` is a purpose built Docker image for debugging R memory problems. Eddelbuettel (2019) describes how a Docker container was used to debug an issue with a package only occurring with a particular version of Fortran, and using tools which are not readily available on all platforms (e.g., not on macOS).

The R-hub Docker images (see Section [Non-Debian Linux images](#)) can also be used to debug problems locally using various combinations of Linux platforms, R versions, and compilers²⁵. See <https://r-hub.github.io/rhub/articles/local-debugging.html> and <https://blog.r-hub.io/2019/04/25/r-devel-linux-x86-64-debian-clang/>. The images go beyond the configurations, or *flavours*, used by CRAN for checking packages²⁵, e.g., with CentOS-based images, but lack a container for checking on Windows or OS X. The images greatly support package developers to provide support on operating systems they are not familiar.

Conclusions

This article is a snapshot of the R-corner in a universe of applications built many-faced piece of software, Docker. Docker became synonymous with applying the concept of containerisation to solve many challenges, such as reproducible environments in research, scalable deployments in heterogenous organisations, and the ability to move processing between machines easily (e.g., locally, one cloud providers VM, another cloud provider's Container-as-a-Service). These are probably the three common themes described in this work.

The R packages and use cases presented show the positive drive in the community to innovate, but also the challenge of keeping up with continuous evolving landscape. The use cases contributed by co-authors also have a degree of overlap. A common language and understanding of good practices is still taking shape. The easiness with which one can create a complex software systems, such as an independent Docker image stack, to serve one's specific needs currently leads to some fragmentation. It is unclear if Docker alone as a core technology is really a feasible level of collaboration and abstraction. Furthermore fragmentation may not be a bad sign but instead a reflection of a growing market, which is able to sustain multiple related efforts. With the maturing of core building blocks, such as the Rocker suite of images, more systems will be built successfully but will also be behind the curtains.

However, at least on the level of R packages, some consolidation seems in order, e.g., to reduce the number of packages creating Dockerfiles from R code or controlling the Docker daemon with R code. It remains to be seen which approach to control Docker, via the Docker API as `stedore` or via system calls as `dockyard`/`docker`/`dockr`, is more sustainable, or if the question will be answered by the endurance of maintainers and sufficient funding. Similarly, the capturing of environments and their serialization in form of a Dockerfile currently happens at different levels of abstraction and re-use of functionality seems reasonable, e.g. `liftr` could generate the environment with `containerit`, which in turn may use `dockerfiler` for low level objects representing a Dockerfile. In this consolidation, the Rocker Project could play the role of a unifying and coordinating entity in the future. Though for the moment, the sign of the times points to more experimentation and feature growth, e.g. images for GPU-based computing and artificial intelligence. Even with coding being more and more accepted as a required, and achievable skill, an easier access, for example by exposing containerisation benefits via simple user interfaces in the users' IDE, could be an important next step. Currently containerisation happens more in the background at the system level.

New features, which make complex workflows accessible and reproducible, and variety in packages, even when they have overlapping features, are a signal and a support for a growing user base. This growth is possibly the the most important goal for the foreseeable future in the *Rockerverse*. The dominant position of Docker is a blessing and a curse for these goals. It could be wise to start experimenting with non-Docker containerisation tools now, e.g. R packages interfacing with other container

²⁵https://cran.r-project.org/web/checks/check_flavors.html

engines such as [podman/buildah](#) or [rkt](#), or an R package for creating Singularity image recipe files. Such efforts help to avoid lock-in and to design sustainable workflows based on concepts of *containerization*, not on their implementation in Docker. If adoption of containerisation and R continue to grow, the missing pieces for a success predominantly lie in (a) coordination and documentation of activities to reduce repeated work in favour of open collaboration, (b) the sharing of lessons learned from use cases to build common knowledge and language, and (c) a sustainable continuation and funding for all of development, community support, and education. A concrete effort by this work towards these pieces is to sustain the structure and captured status quo in a CRAN Task View *Containerization*.

Author contributions

DN conceived of the presented idea and [initialised the formation of the writing team](#), wrote sections not mentioned below, and revised the full first draft. CB .. RC and EH wrote the section on interfaces for Docker in R. DE wrote the introduction and section about Rocker. ME .. CF wrote the paragraphs about [r-online](#), [dockerfiler](#), [r-ci](#) and [r-db](#). BW .. KR .. NR .. NX wrote the section on [liftr](#). LS & NT wrote the section on Bioconductor. All authors contributed minor edits, gave feedback on other sections, and approved the final version.

This articles was collaboratively written at <https://github.com/nuest/rockerverse-paper/>. The [contributors page](#), [commit history](#), and [discussion issues](#) provide a detailed view on the respective contributions.

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