

The Rockerverse: Images, Packages, and Applications for Containerization with R

by Daniel Nüst, Dom Bennett, Robrecht Cannoodt, Dav Clark, Gergely Daroczi, Dirk Eddelbuettel, Mark Edmondson, Colin Fay, Ellis Hughes, Sean Lopp, Ben Marwick, Heather Nolis, Jacqueline Nolis, Hong Ooi, Karthik Ram, Noam Ross, Lori Shepherd, Nitesh Turaga, Nan Xiao

Abstract The R Project provides widely-used Docker images for R across different application scenarios. This article surveys downstream projects building upon R Project and presents the current state of R packages for managing Docker images and controlling containers. We also look beyond R Project to other projects connecting containerisation with R, namely alternative suites of images. These use cases and the variety of applications demonstrate the power of R Project specifically and containerisation in general. We identified common themes across this diversity: reproducible environments, scalability and efficiency, and portability across clouds.

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—in fact, Docker can be called the *lingua franca* of describing computing environments and packaging software. Combining both these topics, the R Project (<https://www.r-project.org/>) provides images with R (see the next Section for more details). The considerable uptake and continued evolution of the R Project has led to numerous projects extending or building upon R Project images, ranging from reproducible research\footnote{"Reproducible" in the sense of the Claerbout/Donoho/Peng terminology (Barba, 2018).} 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 R 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 indirectly 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.

Containerization and R Project

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 virtualization (Wikipedia contributors, 2020).

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>

⁴<https://en.wikipedia.org/wiki/LXC>

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 there more efficiently too (Microsoft, 2019b). The success even lead 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 lead to widespread adoption and use of Docker in a variety of domains, e.g., cloud computing infrastructure (e.g., Bernstein, 2014), data science (e.g., Boettiger, 2015), and edge computing (e.g., Alam et al., 2018). It provided 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 rocker/geospatial (Boettiger et al., 2019). These containers form *image stacks*, building on top of each other for better maintainability (i.e., smaller Dockerfiles), composability, and to reduce build time. 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 projects’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 Server. 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.

Container images

Images for alternative R engines

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 in academia and industry exist to test new approaches, or provide features different to what the R implementation maintained by the R Core Team and available via CRAN provides. 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 others. All these alternative implementations of R are published under GPL licenses. Since all implementations of R 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.

Microsoft R Open (MRO) is an R distribution formerly known as Revolution R Open (RRO) before

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

Revolution Analytics was acquired by Microsoft. MRO is compatible with main R and its packages and it “[...] includes additional capabilities for improved performance, reproducibility, and platform support.” (Microsoft, 2019c) Most notably these capabilities are the MRAN repository, which is enabled by default, and some bundled packages such as **checkpoint** and specific R packages maintained by Microsoft⁶. Originally the optional integration with Intel® Math Kernel Library (MKL) for multi-threading in linear algebra operations (Microsoft) was a distinguishing feature before it was made available publicly, and can be used in base R, too (Eddelbuettel, 2018).

MRO does not provide official Docker images, but a set of community-maintained Dockerfiles and Docker images are provided by the project mro-docker (<https://github.com/nuest/mro-docker>), e.g., the image `nuest/mro`. 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 integration into enterprise platforms. 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`⁷. 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 (<http://www.pqr-project.org/>) 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 differentiation⁸. 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` image was independently created, see Docker Hub at <https://hub.docker.com/r/nuest/pqr/> and GitHub at <https://github.com/nuest/pqr-docker>.

FastR (<https://github.com/oracle/fastr>) is “A high-performance implementation of the R programming language, built on GraalVM” (Oracle Labs, 2020). 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 R (Oracle Labs, 2020). There are no official Docker images provided, but independently maintained experimental images and Dockerfiles are provided by `nuest/fastr-docker`, e.g., `nuest/fastr` on Docker Hub.

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 semi-annual release cycle, each release is associated with a particular version of R. Docker images allow availability of current and past versions of *Bioconductor* for convenience and reproducibility. *Bioconductor*’s ‘base’ docker images are built on top of `rocker/r-ver` and `rocker/rstudio` images. *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 (see <https://bioconductor.org/help/docker/>), created with Dockerfiles maintained on GitHub (https://github.com/Bioconductor/bioconductor_docker), and distributed through DockerHub. Past and current combinations of R and *Bioconductor* are therefore accessible via a specific image tag. 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 may be valuable in teaching, where participants pull pre-built images to avoid complicated configuration of their own computing environments.

⁶See “Bundled Packages” on <https://mran.microsoft.com/rro/installed>.

⁷<http://packages.renjin.org/package/org.renjin.cran/rgdal/1.4-4/build/1>

⁸<https://riotworkshop.github.io/abstracts/riot-2019-pqr.txt>

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 a Ruby templating engine is used for the Dockerfiles. 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.

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 freezed (i.e., using MRAN) versions with only the major and minor version¹⁰. So, at the time of 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*

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>.

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

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:ltsc2019-3.6.2` or `nuest/rocker-win:1803-latest`, and run the R.exe process by default. All these images can be run on Docker for Desktop on Windows 10. New R versions are only added on demand. The explorative rocker-win project demonstrates the variety of Windows on Docker, which is potentially confusing, e.g., because of the different base images. The proof of concept provides a starting point for any Windows-constrained user to leverage containerisation, including examples for apps using **plumber**, **Shiny**, or R packages with system dependencies such as **sf**. The latter is quite comfortable and fast actually, compared to the default installation from source on Linux, because CRAN ships pre-compiled binaries for Windows. However, compared to the various Linux images, the footprint of Windows images is quite large.

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, and the licensing impacts the potential to build images in clouds or redistribute exported images as archive files. 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.

Non-Rocker 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.

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>

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>

RStudio also maintains a set of **Docker images** for multiple operating systems including SUSE, Ubuntu, CentOS, and Debian. The image stack includes an **opinionated R installation** and ensures the R installation and profile is consistent across the different Linux distributions. The base image also installs R in a versioned directory and uses 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 TERR²².

Data Science images

Data Science is a widely discussed topic among all academic disciplines (e.g., Donoho, 2017). The discussions shed a light on the tools and craftsmanship behind the analysis of data with computational methods. The practice of Data Science often involves a combination tools and software stacks and requires a cross-cutting skillset. This complexity and an inherent concern for openness and reproducibility in the Data Science community lead to Docker being used widely. This section presents exemplary Docker images and image stacks featuring R intended for Data Science.

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 naturally also the **IRKernel** (<https://irkernel.github.io/>), an R kernel for Jupyter so that Jupyter Notebooks can contain R code cells. R is also included in the catchall **jupyter/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. R is installed using the Conda package manager, which can manage environments for various programming languages, pinning both the R version and the versions of R packages²⁴.

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 (see also image **rocker/ml** in Section **Common or public work environments**), 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 out²⁵. 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

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>.

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

²⁴See **jupyter/datascience-notebook's Dockerfile** at <https://github.com/jupyter/docker-stacks/blob/master/datascience-notebook/Dockerfile#L47>.

²⁵Originally, 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>

favours inclusion over selection and features Python, Postgres, JupyterLab and Visual Studio Code besides R and RStudio, bringing the image size up to 9GB.

Gigantum (<http://gigantum.com/>) is a platform for open and decentralized data science with a focus on using automation and user-friendly tools for easy sharing of reproducible computational workflows. Gigantum builds on the *Gigantum Client* (running either locally or on a remote server) for development and execution of data-focused *Projects*, which can be stored and shared via the *Gigantum Hub* or via a zipfile export. The Client is a user friendly interface to a backend using Docker containers to package, build, and run Gigantum projects. It is configured to use a default set of Docker base images (<https://github.com/gigantum/base-images>), and users are able to define and configure their own custom images. The available images include two with R based on Ubuntu Linux have the `c2d4u` CRAN PPA pre-configured for installation of binary R packages²⁶. The R images vary in the included authoring environment, i.e., Jupyter in `r-tidyverse` or both Jupyter & RStudio in `rstudio-server`. The independent image stack can be traced back to the Gigantum environment and its features. The R images are based on Gigantum's `python3-minimal` image, originally to keep the existing front-end configuration, but also to provide a consistent Python-to-R interoperability. The Dockerfiles also use build args to specify bases, for example for different version of NVIDIA CUDA for GPU processing²⁷ so that appropriate GPU drivers can be enabled automatically when supported. Furthermore, Gigantum's focus lies on environment management via GUI and ensuring a smooth user interaction, e.g., with reliable and easy conflict detection and resolution. For this reason, project repositories store authoritative package information in a separate file per package, allowing Git to directly detect conflicts and changes. A Dockerfile is generated from this description that inherits from the specified base image, and additional custom Docker instructions may be appended by users, though Gigantum's default base images do not currently include the `littler` tool, which is used by Rocker to install packages within Dockerfiles. Because of these specifics, instructions from `rocker/r-ubuntu` could *not* be readily re-used in this image stack (see Section ??). Both approaches enable apt as an installation method, and this is exposed via the GUI-based environment management²⁸. The image build and publication process is scripted with Python and JSON template configuration files, unlike Rocker which relies on plain Dockerfiles. A minor reason in the inception of the images were also project constraints requiring a Rocker-incompatible licensing of the Dockerfiles, i.e., the MIT License.

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 a 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.

²⁶<https://docs.gigantum.com/docs/using-r>

²⁷See https://github.com/gigantum/base-images/blob/master/_templates/python3-minimal-template/Dockerfile for the Dockerfile of `python3-minimal`.

²⁸See <https://docs.gigantum.com/docs/environment-management>

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			✓			

harbor (<https://github.com/wch/harbor>) is not actively maintained anymore, but should be honorably mentioned as the first R package for managing Docker images and containers. It uses the **sys** package to run system commands against the Docker CLI, both locally and through an ssh connection, and has convenience functions, e.g., for listing and removing containers/images and for accessing logs. The output of container executions are converted to appropriate R types. The Docker CLI, while evolving quickly and not with great concern for introducing breaking changes, basic functionality is unchanged for a long time so `harbor::docker_run(image = "hello-world")` works like a charm.

stevedore (<https://cran.r-project.org/package=stevedore>) is currently the most powerful Docker client in R. It interfaces with the Docker daemon over the Docker HTTP API²⁹ via a Unix socket on Linux or MacOS, over a named pipe on Windows, or over an HTTP/TCP connection. The package is the only one not using system calls to the docker CLI for managing images and containers and easily exposes connections to remote Docker daemons, which has to be configured on the Docker level otherwise. Using the API gives access to more information and is system independent and likely more reliable than parsing command line output. **stevedore**'s own interface is automatically generated based on the OpenAPI specification of the Docker daemon, but still similar to the Docker CLI. The interface is similar to R6 objects, in that a `stevedore_object` has a number of functions attached to it that can be called, and multiple specific versions of the Docker API can be supported thanks to the automatic generation³⁰.

AzureContainers is an interface to a number of container-related services in Microsoft's **Azure Cloud**, see Section [Deployment to the cloud](#). While it is mainly intended for working with Azure, as a convenience feature it includes lightweight, cross-platform shells to Docker and Kubernetes (tools `kubectl` 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 allows executing and interacting with containers, which can use either Docker or Singularity as a backend ([Cannoodt and Saelens, 2019](#)). 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.

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

²⁹<https://docs.docker.com/engine/api/latest/>

³⁰See <https://github.com/richfitz/stevedore/tree/master/inst/spec> and <https://github.com/richfitz/stevedore/blob/master/development>

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 (<https://github.com/ColinFay/dockerfiler/>) ...

containerit (<https://github.com/o2r-project/containerit/>) ...

dockr (<https://github.com/smaakage85/dockr>) ... see/cite <http://smaakage85.netlify.com/2019/12/21/dockr-easy-containerization-for-r/>

renv (<https://rstudio.github.io/renv/>) with Docker: <https://rstudio.github.io/renv/articles/docker.html>

version pinning with packages **remotes** and **versions** for R, and with system package managers for distros

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 1.

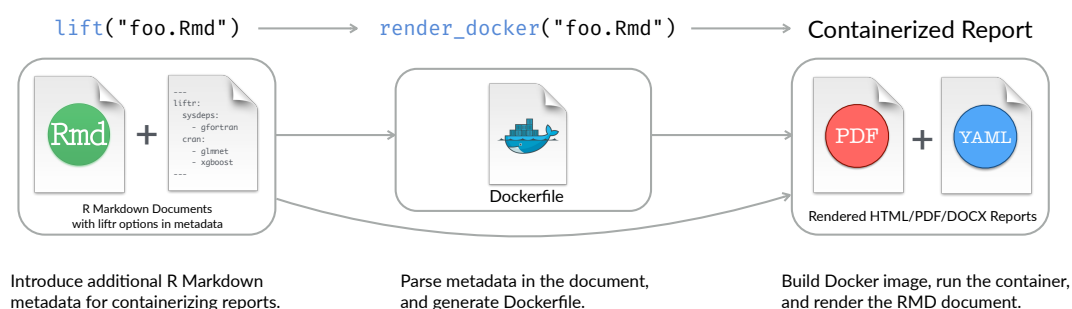


Figure 1: The *liftr* workflow for rendering containerized R Markdown documents.

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 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 containeriza-

tion, 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.

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 with the ability to deploy R in Docker containers, modern enterprises are now capable of having real-time machine learning powered by R. One of the first implementations of having R respond to client requests were TCP/IP and local socket servers, such as *Rserve* and *svSocket*, which allowed other local or remote processes to make binary requests to interact with R without the need to link to R at compile time and connected other programming languages with R. R could also empower web services since at least 2007, when *rApache* was presented at the useR! conference (Horner, 2013). *rApache* runs an R interpreter inside the Apache web server, which makes it possible and very efficient to build scalable R-based APIs and web services.

Such *rApache* applications have been used at *rapporter.net*, transforming parametrized R Markdown-like documents into interactive web applications for reporting. A similar design was implemented at *CARD.com*, where the optimization of the acquisition flow and the real-time analysis of debit card transactions both relied on an efficient combination of *Rserve* and *rApache* running in Docker containers: the R session behind *Rserve* acted as a read-only, extremely fast and scalable, in-memory database for the many concurrent *rApache* processes responding to the live-scoring requests of various divisions of the company. Similar dockerized R scripts were responsible for the ETL processes and even the client-facing email, text message and push notification alerts sent in real-time based on card transactions. The related Docker images were made available at <https://github.com/cardcorp/card-rocker>. The images extend *rocker/r-base*, e.g., with an SSH client and a workaround for being able to mount SSH keys from the host, Pandoc, the Amazon Web Services (AWS) SDK, and Java, which is required by the AWS SDK. The AWS SDK allowed to run R consumers reading from real-time data processing streams of *AWS Kinesis*. The applications were deployed on Amazon Elastic Container Service (ECS). The main learnings from using R in Docker was the importance of not only pinning the R package versions via MRAN, but also moving away from Debian testing to an LTS distribution. For the use case at hand, the priority was to have more control over upstream updates, and to minimize the risk of breaking the automated builds of the Docker images and production jobs.

A more recent related work is the *plumber* (<https://www.rplumber.io/>) package, which makes it even easier for 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](#).

[RestRserve](#) is an alternative R web API framework with the main focus on being high-performant and robust. It also ships automated Docker builds at <https://hub.docker.com/r/rexyai/restrserve/dockerfile>.

Deployment to the cloud

The cloud is the natural environment of containers, and is the natural mechanism to deploy R server applications.

- [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](#) is an umbrella package providing interfaces the three services of Microsoft's Azure Cloud, namely [Container Instances](#) for running individual containers, [Container Registry](#) for private image distribution, and [Kubernetes Service](#) for orchestrated deployments. While a package like [plumber](#) provides the infrastructure for turning an R workflow a service, for production purposes it is usually necessary to take into account scalability, reliability and ease of management. A single container is limited in the volume of requests it can service, and if the container goes down or is occupied with processing a computationally intensive task, the service becomes unavailable. These issues can be mitigated by deploying not a single container, but a *cluster* of containers, orchestrated as a single deployment, e.g., with [Kubernetes](#). A cluster features load-balancing, autoscaling of containers across numerous servers (in the cloud or on premise), and restarting failed ones. 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, and to Kubernetes' `kubect1` and `helm` tools, that are needed for managing Kubernetes clusters. The package simplifies complex infrastructure management to a number of R function calls,

given an Azure account with sufficient credit³¹.

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.
 - <https://code.markedmondson.me/googleCloudRunner/articles/cloudbuild.html>

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 short cicuits 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.

³¹See "Deploying a prediction service with Plumber" vignette for details: https://cran.r-project.org/web/packages/AzureContainers/vignettes/vig01_plumber_deploy.html.

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 in 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 (ML) tasks, e.g., deep artificial neural networks (Schmidhuber, 2015). Though in this case, containers are not completely portable between hardware environments, but the software stack for ML with GPUs is so complex to set up that a ready-to-use container is helpful. 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 a repository with (beta) images based on these that include GPU-enabled versions of machine-learning R packages, e.g., rocker/ml and rocker/tensorflow-gpu.

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 (<https://rcloud.social>) is a cloud-based platform for data analysis, visualisation and collaboration using R. It provides a rocker/drd base image for easy evaluation of the platform³².

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.

³²<https://github.com/att/rcloud/tree/master/docker>

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 R sessions 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

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.
 - How does this relate to <https://code.markedmondson.me/googleCloudRunner/index.html>?
- [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>

Packaging programs for processing pipelines

Docker is perfectly suited for packaging and executing any software and data, and is a good candidate for building complex processing pipelines that are independent from the host programming language.

Due to its original use case (see [Introduction](#)), Docker has no standard mechanisms for chaining containers together; it lacks definitions and protocols for environment variables, volume mounts and/or ports that could enable transfer of input (parameters and data) and output (results) to and from containers. Some packages, e.g., **containerit**, do provide Docker images that can be used similarly to CLIs, but their usage is cumbersome³³.

outsider (<https://antonellilab.github.io/outsider/>) tackles the problem of integrating external programs into an R workflow (Bennett et al., 2020). Installation and usage of external programs can be difficult, convoluted and even impossible if the platform is incompatible. Therefore **outsider** uses the platform-independent Docker images to encapsulate processes in *outsider modules*. Each outsider module has a Dockerfile and an R package with functions for interacting with the encapsulated tool. Using only R functions, an end-user can install a module with the **outsider** package and then call module code to integrate a tool into their own R-based workflow seamlessly. The **outsider** package and module manage the containers and handle the transmission of arguments and the transfer of files to and from a container. These functionalities also allow a user to launch module code on a remote machine via SSH, expanding the potential computational scale. Outsider modules can be hosted code-sharing services, e.g., on GitHub, and **outsider** contains discovery functions for them.

Research Compendia

- researchcompendia.science
- <https://github.com/benmarwick/rrtools>
- **renv**, <https://rstudio.github.io/renv/articles/docker.html>
- what to copy in and what not

Development and debugging

Containers can also serve as useful playgrounds to create environments ad-hoc or to provide very specific environments that are not needed or not easily available in day-to-day development. These environments may have specific versions of R, of R extension packages, and of system libraries used by R extension packages, and all of the above in a specific combination.

First, such containers can greatly facilitate **fixing bugs**, because developers can readily start and later discard a container to investigate a bug report without affecting their regular system, and potentially having to revert changes back. Using the Rocker images with RStudio, these disposable environments lack no development comfort (cf. Section [Research Compendia](#)). Eddelbuettel (2019) describes an example 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). For the [R-spatial community](#), using containers is particularly useful, because of the strong integration of system libraries in core packages for geospatial data modelling and analysis. Purpose built Docker are used to prepare for upcoming releases of system libraries, individual bug reports, and for the lowest supported versions of system libraries³⁴.

There are also special images for identifying problems beyond the mere R code, such as **debugging R memory problems**. The images significantly reduce the barrier to follow complex steps for fixing memory allocation bugs (cf. Section 4.3 in [R Core Team, 1999](#)). These problems are hard to debug and critical, both because when they occur they lead to fatal crashing processes. [rocker/r-devel-san](#) and [rocker/r-devel-ubsan-clang](#) are Docker images have a particularly configured version of R to trace such problems with gcc and clang compilers, respectively (cf. [sanitizers](#) for examples, Eddelbuettel, 2014). The image [wch/r-debug](#) is a purpose built Docker image with *multiple* instrumented builds of R, each with a different diagnostic utility activated.

Second, containers are useful for **testing** R code during development. To submit a package to CRAN, an R package must work with the development version of R, which must be compiled locally. That can be a challenge for some users. The R-hub service (see Section [Non-Rocker Linux images](#)) makes it easy to ensure that no errors occur, but to fix errors a local setup is still often warranted, e.g., using the image [rocker/r-devel](#), and to test packages with native code, which can make the process more complex (cf. Eckert, 2018). The R-hub Docker images can also be used to debug problems locally using various combinations of Linux platforms, R versions, and compilers³⁵. The images go beyond the configurations, or *flavours*, used by CRAN for checking packages³⁶, e.g., with CentOS-based

³³<https://o2r.info/containerit/articles/container.html>

³⁴Cf. <https://github.com/r-spatial/sf/tree/master/inst/docker>, https://github.com/Nowosad/rsatial_proj6, and <https://github.com/r-spatial/sf/issues/1231>

³⁵See <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/>

³⁶https://cran.r-project.org/web/checks/check_flavors.html

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. The package **dockertest** (<https://github.com/traitecoevo/dockertest/>) is a proof of concept for automatically generating Dockerfiles and building images specifically to run tests³⁷. These images are accompanied with a special launch script so the tested source code is not stored in the image but the currently checked in version from a local Git repository is cloned into the container at runtime. This approach clearly separates test environment, test code, and current working copy of the code.

Third, Docker images can be used on **CI platforms** to streamline the testing of packages. Ye (2019) describes how they speed up the process of testing by running tasks on Travis CI within a container using `docker exec`, e.g., the package check or rendering of documentation. Cardozo (2018), also on Travis CI saved time by re-using the testing image as the base image for an image intended for publication on Docker Hub. Especially for long running tests or complex system dependencies, these approaches seems to improve the development. Not due to a concern about time, but to control the environment used on a CI server, even this manuscript was rendered into a PDF and deployed to a GitHub-hosted website (see `.travis.yml` and `Dockerfile` in the manuscript repository). This gives on the one hand easy access after every update of the R Markdown source code, and on the other hand a second controlled environment making sure that the article renders successfully and correctly.

Conclusions

This article is a snapshot of the R-corner in a universe of applications built many-faced piece of software, Docker. Dockerfiles and Docker images are the go-to methods for collaboration between roles in an organisation, such as development and IT operations teams, and between parties in the communication of knowledge, such as research workflows or education. Docker became synonymous with applying the concept of containerisation to solve challenges of reproducible environments, e.g., in research and in development & production, and of scalable deployments with the ability to move processing between machines easily (e.g., locally, one cloud providers VM, another cloud provider's Container-as-a-Service). Reproducible environments, scalability and efficiency, and portability across clouds are the common themes behind R packages, use cases, and applications 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 a continuously evolving landscape. The use cases contributed by co-authors also have a degree of overlap, which can be expected as a common language and understanding of good practices is still taking shape. Also, the ease with which one can create a complex software systems with Docker, such as an independent Docker image stack, to serve one's specific needs leads to parallel developments. This ease-of-DIY in combination with the difficulty to compose environments based on Dockerfiles alone is a further reason for **fragmentation**. Instructions can be outsourced into distributable scripts and then copied into the image during build, but that make Dockerfile hard to read and adds a layer of complexity. Despite the different image stacks presented here, the pervasiveness of Docker can be traced back to its maintainers and the user community valuing collaboration and shared starting points over impulses to create individual solutions. Aside from that, 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 Docker suite of images, more systems will be built successfully but will also be behind the curtains. Docker alone, as a flexible core technology, is not a feasible level of collaboration and abstraction. Instead, the use cases and applications observed in this work provide a more useful division.

Nonetheless, 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 `dockfiler` for low level objects representing a Dockerfile. In this consolidation, the Docker Project could play the role of coordinating entity. 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 the variety in

³⁷**dockertest** is not actively maintained, but mentioned still because of its interesting approach.

packages connected with containerisation, even when they have overlapping features, are a signal and a support for a growing user base. This growth is possibly the most important goal for the foreseeable future in the *Rockerverse*, and just like the Rocker images have matured over years of use and millions of runs the new ideas and prototypes will have to prove themselves. It should be noted that 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 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 *containerisation*, 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 to work towards these pieces is to sustain the structure and captured status quo from this work in form of a *CRAN Task View on containerization*.

Author contributions

The ordering of authors following DN as first author is alphabetical. DN conceived the article idea, [initialised the formation of the writing team](#), wrote sections not mentioned below, and revised all sections. DB wrote the section on **outsider**. GD contributed the CARD.com use case. DE wrote the introduction and the section about Containerization and Rocker. RC & EH contributed to the section on interfaces for Docker in R. DC contributed content on Gigantum. ME contributed to the section on processing and deployment to cloud services. CF wrote paragraphs about **r-online**, **dockerfiler**, **r-ci** and **r-db**. BM wrote the section on research compendia and made the project Binder-ready. HN & JN co-wrote the section on enterprise production environments (**googleComputeEngineR**, Google Cloud Run, Kubernetes). KR wrote the section about **wholepunch**. NR wrote paragraphs about shared work environments and GPUs. LS & NT wrote the section on Bioconductor. NX wrote the section on **liftr**. All authors approved the final version. This article 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.

Acknowledgements

DN is supported by the project Opening Reproducible Research ([o2r](#)) funded by the German Research Foundation (DFG) under project number [PE 1632/17-1](#). The funders had no role in data collection and analysis, decision to publish, or preparation of the manuscript.


Bibliography


- GraalVM, Aug. 2019. URL <https://en.wikipedia.org/w/index.php?title=GraalVM&oldid=912552499>. Page Version ID: 912552499. [p3]
- M. Alam, J. Rufino, J. Ferreira, S. H. Ahmed, N. Shah, and Y. Chen. Orchestration of Microservices for IoT Using Docker and Edge Computing. *IEEE Communications Magazine*, 56(9):118–123, Sept. 2018. ISSN 0163-6804, 1558-1896. doi: 10.1109/MCOM.2018.1701233. [p2]
- L. A. Barba. Terminologies for Reproducible Research. *arXiv:1802.03311 [cs]*, Feb. 2018. URL <http://arxiv.org/abs/1802.03311>. arXiv: 1802.03311. [p1]
- D. Bennett, H. Hettling, D. Silvestro, R. Vos, and A. Antonelli. *outsider: Install and run programs, outside of r, inside of r* (under review). *Journal of Open Source Software*, 2020. [p15]
- D. Bernstein. Containers and cloud: From LXC to docker to kubernetes. *IEEE Cloud Computing*, 1(3): 81–84, Sept. 2014. doi: 10.1109/mcc.2014.51. [p2]
- C. Boettiger. An introduction to Docker for reproducible research, with examples from the R environment. *ACM SIGOPS Operating Systems Review*, 49(1):71–79, Jan. 2015. ISSN 01635980. doi: 10.1145/2723872.2723882. [p2, 4]
- C. Boettiger and D. Eddelbuettel. An Introduction to Rocker: Docker Containers for R. *The R Journal*, 9(2):527–536, 2017. doi: 10.32614/RJ-2017-065. [p2, 4]

- C. Boettiger, R. Lovelace, M. Howe, and J. Lamb. rocker-org/geospatial, Dec. 2019. [p2]
- R. Cannoodt and W. Saelens. *babelwhale: Talking to 'Docker' and 'Singularity' Containers*, 2019. URL <https://CRAN.R-project.org/package=babelwhale>. R package version 1.0.1. [p8]
- L. Cardozo. Faster Docker builds in Travis CI for R packages, 2018. URL <https://lecardoza.github.io/2018/03/01/automated-docker-build.html>. [p16]
- Chan Zuckerberg Initiative, C. Boettiger, N. Ross, and D. Eddelbuettel. Maintaining Rocker: Sustainability for Containerized Reproducible Analyses, 2019. URL <https://chanzuckerberg.com/eoss/proposals/maintaining-rocker-sustainability-for-containerized-reproducible-analyses/>. [p2]
- G. Csárdi and M. Salmon. *rhub: Connect to 'R-hub'*, 2019. URL <https://CRAN.R-project.org/package=rhub>. R package version 1.1.1. [p5]
- Datadog. 8 surprising facts about real Docker adoption, June 2018. URL <https://www.datadoghq.com/docker-adoption/>. [p1, 2]
- D. Donoho. 50 Years of Data Science. *Journal of Computational and Graphical Statistics*, 26(4):745–766, Oct. 2017. ISSN 1061-8600. doi: 10.1080/10618600.2017.1384734. URL <https://doi.org/10.1080/10618600.2017.1384734>. [p6]
- A. Eckert. Building and testing R packages with latest R-Devel, Feb. 2018. URL <https://alexandereckert.com/post/testing-r-packages-with-latest-r-devel/>. [p15]
- D. Eddelbuettel. *sanitizers: C/C++ source code to trigger Address and Undefined Behaviour Sanitizers*, 2014. URL <https://CRAN.R-project.org/package=sanitizers>. R package version 0.1.0. [p15]
- D. Eddelbuettel. Thinking inside the box, Apr. 2018. URL <http://dirk.eddelbuettel.com/blog/2018/04/15/>. [p3]
- D. Eddelbuettel. Debugging with Docker and Rocker – A Concrete Example helping on macOS, Aug. 2019. URL <http://dirk.eddelbuettel.com/blog/2019/08/05/>. [p15]
- W. Felter, A. Ferreira, R. Rajamony, and J. Rubio. An updated performance comparison of virtual machines and Linux containers. In *2015 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS)*, pages 171–172, Mar. 2015. doi: 10.1109/ISPASS.2015.7095802. [p2]
- R. C. Gentleman, V. J. Carey, D. M. Bates, B. Bolstad, M. Dettling, S. Dudoit, B. Ellis, L. Gautier, Y. Ge, J. Gentry, K. Hornik, T. Hothorn, W. Huber, S. Iacus, R. Irizarry, F. Leisch, C. Li, M. Maechler, A. J. Rossini, G. Sawitzki, C. Smith, G. Smyth, L. Tierney, J. Y. Yang, and J. Zhang. Bioconductor: open software development for computational biology and bioinformatics. *Genome Biology*, 5(10):R80, Sept. 2004. ISSN 1474-760X. doi: 10.1186/gb-2004-5-10-r80. [p3]
- N. Haydel, G. Madey, S. Gesing, A. Dakkak, S. G. de Gonzalo, I. Taylor, and W.-m. W. Hwu. Enhancing the Usability and Utilization of Accelerated Architectures via Docker. In *Proceedings of the 8th International Conference on Utility and Cloud Computing, UCC '15*, pages 361–367. IEEE Press, 2015. ISBN 978-0-7695-5697-0. URL <http://dl.acm.org/citation.cfm?id=3233397.3233456>. [p13]
- J. Horner. *rApache: Web application development with R and Apache.*, 2013. URL <http://www.rapache.net/>. [p10]
- K. Hornik, U. Ligges, and A. Zeileis. Changes on cran. *The R Journal*, 11(1):438–441, June 2019. URL <http://journal.r-project.org/archive/2019-1/cran.pdf>. [p1]
- P. Jupyter. Jupyter Docker Stacks — docker-stacks latest documentation, 2018. URL <https://jupyter-docker-stacks.readthedocs.io/en/latest/>. [p6]
- P. Jupyter, M. Bussonnier, J. Forde, J. Freeman, B. Granger, T. Head, C. Holdgraf, K. Kelley, G. Nalvarte, A. Osherooff, M. Pacer, Y. Panda, F. Perez, B. Ragan-Kelley, and C. Willing. Binder 2.0 - Reproducible, interactive, sharable environments for science at scale. *Proceedings of the 17th Python in Science Conference*, pages 113–120, 2018. doi: 10.25080/Majora-4af1f417-011. [p12]
- G. M. Kurtzer, V. Sochat, and M. W. Bauer. Singularity: Scientific containers for mobility of compute. *PLOS ONE*, 12(5):e0177459, May 2017. ISSN 1932-6203. doi: 10.1371/journal.pone.0177459. [p1, 2]
- M. Lang, B. Bischl, and D. Surmann. batchtools: Tools for r to work on batch systems. *The Journal of Open Source Software*, 2(10):135, 2 2017. ISSN 2475-9066. doi: 10.21105/joss.00135. [p14]

- S. Lopp. Package Manager 1.1.0 - No Interruptions, Jan. 2019. URL <https://blog.rstudio.com/2019/11/07/package-manager-v1-1-no-interruptions/>. [p6]
- B. Marwick, C. Boettiger, and L. Mullen. Packaging Data Analytical Work Reproducibly Using R (and Friends). *The American Statistician*, 72(1):80–88, Jan. 2018. ISSN 0003-1305, 1537-2731. doi: 10.1080/00031305.2017.1375986. [p13]
- Microsoft. The Benefits of Multithreaded Performance with Microsoft R Open . MRAN. URL <https://mran.revolutionanalytics.com/documents/rro/multithread>. [p3]
- Microsoft. CRAN Time Machine - MRAN, 2019a. URL <https://mran.microsoft.com/timemachine>. [p2]
- Microsoft. Linux Containers on Windows, Sept. 2019b. URL <https://docs.microsoft.com/en-us/virtualization/windowscontainers/deploy-containers/linux-containers>. [p2]
- Microsoft. About Microsoft R Open: The Enhanced R Distribution . MRAN, 2019c. URL <https://mran.revolutionanalytics.com/rro>. [p3]
- S. Muñoz. The history of Docker’s climb in the container management market, June 2019. URL <https://searchservervirtualization.techtarget.com/feature/The-history-of-Dockers-climb-in-the-container-management-market>. [p1]
- D. Nüst. nüst/rocker-win: Proof on concept for R in Windows-based Docker Containers, Dec. 2019. URL <https://doi.org/10.5281/zenodo.3584107>. [p5]
- OCI. Open Containers Initiative - About, 2019. URL <https://www.opencontainers.org/about>. [p2]
- Oracle Labs. oracle/fastr, Jan. 2020. URL <https://github.com/oracle/fastr>. [p3]
- R Core Team. *Writing R extensions*, 1999. URL <https://cran.r-project.org/doc/manuals/r-devel/R-exts.html>. [p15]
- R-hub project. R-hub Docs, 2019. URL <https://docs.r-hub.io/>. [p5]
- A. Ratesic. Building a Repository of Alpine-based Docker Images for R, Part II – Curiosity Killed the Cat – (... but satisfaction brought it back.), Nov. 2018. URL <https://velaco.github.io/my-dockerfile-for-r-shiny-based-on-alpine-linux-II/>. [p6]
- J. Schmidhuber. Deep learning in neural networks: An overview. *Neural Networks*, 61:85–117, Jan. 2015. ISSN 0893-6080. doi: 10.1016/j.neunet.2014.09.003. [p13]
- T-Mobile, J. Nolis, and H. Nolis. Enterprise Web Services with Neural Networks Using R and TensorFlow, Nov. 2018. URL <https://opensource.t-mobile.com/blog/posts/r-tensorflow-api/>. [p11]
- H. Wickham, M. Averick, J. Bryan, W. Chang, L. McGowan, R. François, G. Golemund, A. Hayes, L. Henry, J. Hester, M. Kuhn, T. Pedersen, E. Miller, S. Bache, K. Müller, J. Ooms, D. Robinson, D. Seidel, V. Spinu, K. Takahashi, D. Vaughan, C. Wilke, K. Woo, and H. Yutani. Welcome to the Tidyverse. *Journal of Open Source Software*, 4(43):1686, Nov. 2019. ISSN 2475-9066. doi: 10.21105/joss.01686. URL <https://joss.theoj.org/papers/10.21105/joss.01686>. [p12]
- Wikipedia. Renjin, Aug. 2018. URL <https://en.wikipedia.org/w/index.php?title=Renjin&oldid=857160986>. Page Version ID: 857160986. [p3]
- Wikipedia contributors. OS-level virtualization, Jan. 2020. URL https://en.wikipedia.org/w/index.php?title=OS-level_virtualization&oldid=935110975. Page Version ID: 935110975. [p1]
- N. Xiao. *liftr: Containerize R Markdown Documents for Continuous Reproducibility*, 2019. URL <https://CRAN.R-project.org/package=liftr>. R package version 0.9.2. [p9]
- Y. Xie, J. J. Allaire, and G. Golemund. *R Markdown: The Definitive Guide*. Chapman and Hall/CRC, 2018. [p9]
- H. Ye. Docker Setup for R package Development, 2019. URL <https://haoye.us/post/2019-10-10-docker-for-r-package-development/>. [p16]

Daniel Nüst
University of Münster
Institute for Geoinformatics
Heisenbergstr. 2
48149 Münster, Germany
 0000-0002-0024-5046
daniel.nuest@uni-muenster.de

Dom Bennett
University of Gothenburg, Sweden
Department of Biological and Environmental Sciences
Carl Skottsbergs gata 22B
413 19 Gothenburg, Sweden
 0000-0003-2722-1359
dominic.john.bennett@gmail.com

Robrecht Cannoodt
Ghent University
Data Mining and Modelling for Biomedicine group
VIB Center for Inflammation Research
Technologiepark 71
9052 Ghent, Belgium
 0000-0003-3641-729X
robrecht@cannoodt.dev

Dav Clark
Gigantum, Inc.
1140 3rd Street NE
Washington, D.C. 20002, USA
 0000-0002-3982-4416
dav@gigantum.com

Gergely Daroczi
 0000-0003-3149-8537
daroczig@rapporter.net

Dirk Eddelbuettel
University of Illinois at Urbana-Champaign
Department of Statistics
Illini Hall, 725 S Wright St
Champaign, IL 61820, USA
 0000-0001-6419-907X
dirkd@eddelbuettel.com


Mark Edmondson
IIH Nordic A/S, Google Developer Expert for GCP
mark@markedmondson.me

Colin Fay
ThinkR
50 rue Arthur Rimbaud
93300 Aubervilliers, France
 0000-0001-7343-1846
contact@colinfay.me

Ellis Hughes
Fred Hutchinson Cancer Research Center
Vaccine and Infectious Disease
1100 Fairview Ave. N., P.O. Box 19024
Seattle, WA 98109-1024, USA

ehhughes@fredhutch.org

Sean Lopp
RStudio, Inc
250 Northern Ave
Boston, MA 02210, USA
sean@rstudio.com

Ben Marwick
University of Washington
Department of Anthropology
Denny Hall 230, Spokane Ln
Seattle, WA 98105, USA
 0000-0001-7879-4531
bmarwick@uw.edu

Heather Nolis
T-Mobile
12920 Se 38th St.
Bellevue, WA, 98006, USA
heather.wensler1@t-mobile.com

Jacqueline Nolis
Nolis, LLC
Seattle, WA, USA
 0000-0001-9354-6501
jacqueline@nolisllc.com

Hong Ooi
Microsoft
Level 5, 4 Freshwater Place
Southbank, VIC 3006, Australia
hongooi@microsoft.com

Karthik Ram
Berkeley Institute for Data Science
University of California
Berkeley, CA 94720, USA
 0000-0002-0233-1757
karthik.ram@berkeley.edu

Noam Ross
EcoHealth Alliance
460 W 34th St., Ste. 1701
New York, NY 10001, USA
 0000-0002-0233-1757
ross@ecohealthalliance.org

Lori Shepherd
Roswell Park Comprehensive Cancer Center
Elm & Carlton Streets
Buffalo, NY, 14263, USA
 0000-0002-5910-4010
lori.shepherd@roswellpark.org

Nitesh Turaga
Roswell Park Comprehensive Cancer Center
Elm & Carlton Streets
Buffalo, NY, 14263, USA
 0000-0002-0224-9817
nitesh.turaga@roswellpark.org

Nan Xiao
Seven Bridges Genomics
529 Main St, Suite 6610
Charlestown, MA 02129, USA
 0000-0002-0250-5673
me@nanx.me