Building Software Defined Sub Systems with Automated Environment Management

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Abstract

Systems for modern applications require dynamic computing resources for various workload with a different type of datasets and a collection of software work together to complete tasks on IaaS, PaaS, SaaS or FaaS. Building a cluster of virtual machines is inevitable to accelerate computation speed for these applications but there are challenging tasks to deploy, configure and manage systems in a virtualized environment or high performance computing (HPC). DevOps tools provide automated software deployment and continuous integration, yet computing environments and resources for applications need to be prepared manually by system administrator and application developer because of dependency hell. Template-based infrastructure provisioning permits a repeatable build of a virtual system but the execution of applications is separated from the system built which has no trace of workloads. In this dissertation, we combine these two approaches to fully automate from preparing environments to running workload of applications in a structured way which results in building software defined sub systems (SDS) with scripting for automated deployment.

Linux container technologies are introduced to ensure reproducibility using container images stored in a union filesystem and "off the shelf" software deployment is offered to automate building an equivalent software environment across various platforms. Compatibility with HPC is examined regarding to deploying software stacks as well as cloud computing therefore compute environments created by linux containers are provided in a user space without the system administrative effort. In addition, special application domains i.e. big data applications with NIST projects and bioinformatics are explored to demonstrate practical experiences of applying automated software deployments with the philosophy of software defined systems.

Keywords: Automation, Reproducibility, Software Defined Systems, Big Data, Infrastructure Provisioning, Template Deployment, DevOPs, Linux Containers

1 Introduction

From Infrastructure-as-a-Service to Functions-as-a-Service, many efforts have been made to provide computing resources in virtualized environments but with less complication of building infrastructure and preparing environments. Lightweight linux containers are widely adopted in supporting interdisciplinary field of research and collaboration because of its kernel level of an isolated environment. IaaS is a still best approach to operate fine-grained resource provisioning regarding to CPU, memory, storage and network. This thesis will explore the rapid evolution of virtualization technologies from IaaS to serverless computing with container technologies to find optimized configuration of systems with a general software deployment. The next generation system must utilize DevOps tools for deploying software stacks on a cluster of virtual machines and infrastructure provisioning for supporting various applications. In recent years, building big data clusters have become an inevitable task for performing analysis with the increased computational requirements for large datasets and the anticipated systems will be perfect for these situations to every dimension of infrastructure provisioning and software deployment.

Supporting big data analytics is more difficult for a few reasons: (1) big data applications run with large datasets and a collection of software, (2) building and managing big data deployments on clusters require expertise of infrastructure and (3) Apache Hadoop based big data software stacks are not suitable for HPC. In an effort to resolve the first two issues, public datasets and data warehouse on the cloud have offered to ensure instant data access with SQL support and enterprise big data solutions have hosted by cloud providers e.g. Amazon, Google, and Microsoft to save time on deploying multiple software stacks without facing installation errors. These services, however, are only available to their customers and make hard to swtich to another when applications and pipelines are built on top of the services. Pre-developed infrastructure for big data stacks are only suitable for particular use cases and are unable to customize or re-define by users. There are efforts to simplify a deployment with a specification such as automated deployment engines using TOSCA (Wettinger, Breitenbücher, and Leymann, 2015), but they do not integrate multiple clouds with a cluster deployment or a workload execution. The bigdata deployment on clusters require more than single software to install and configure with different roles i.e. masters and workers. If it is built on virtualized resources, scaling up or down is necessary to maximize resource utilization but with exceptional performance.

These issues can be resolved using a template deployments for infrastructure and software which uses YAML or JSON documents to describe installing tools and allocating resources. For example, Amazon OpsWorks uses Chef to deploy software stacks and Cloudformation uses YAML document to deploy Amazon resources. Similarly, Microsoft Resource Manager Templates uses JSON document to deploy Azure resources and Google Cloud deployment Manager uses python or Jinja2 templating language to deploy Google Cloud platform resources. OpenStack heat is originated from AWS Cloudformation to deploy resources but extended with the integration among openstack services e.g. Telemetry for autoscaling. These templates have been used for infrastructure deployment and software installation with input parameters which enables repeatable provisioning on virtual environments. We extend the use of a template with workload execution recording to track workflow steps and replicate results and also a role based deployment for building clusters. This will be beneficial to share scientific pipelines which typically contain complicated and long-running processes. Our approach is to record status and results of components in the workflow while it is running and store the execution information in templates for later use. This allow users to re-run the workflow on different systems but start from where the workflow stopped without executing whole processes again.

This proposal consists of the following sections. First, background introduces basics of a template deployment with big data software stacks, binary containers for hpc, template use cases for public clouds and NIST big data projects. Next, the design section provides a prototype of a template deployment and checkpoint/restart in user space (CRIU) regards to big data software stacks with clusters. The implementation section demonstrates plans to apply the big data template deployments towards clouds and HPC, such as amazon, azure, openstack, google compute and Slurm with integrated specifications. The schedule section provides to-do lists with estimated timelines to be completed. Last, summary section outlines this dissertation.

1.1 Thesis Statement

Software defined systems with DevOps and Template infrastructure provisioning is an effective way of enabling big data software stacks on the cloud and hpc with container technologies.

2 Background

2.1 Software Deployment for dynamic computing environments

Software development has evolved with rich libraries and building a new computing environment (or execution environment) requires set of packages to be successfully installed with minimal efforts. The environment preparation on different infrastructure and platforms is a challenging task because each preparation have individual instructions which build a similar environment, not identical environment. Traditional method of software deployment is using shell scripts to define installation steps with a system package manager command such as apt, yum, dpkg, dnf and make but it is not suitable to deal with large number of packages actively updated and added to community in a universal way. Python Package Index (PyPI) has almost 95,490 packages (as of 12/26/2016) with 40+ daily new packages and github.com where most software packages, libraries and tools are stored has 5,776,767 repositories available with about 20,000 daily added repositories. DevOps tools i.e. Configuration management software supports automated installation with repeatable executions and better error handling compared to bash scripts but there is no industry standards for script formats and executions. Puppet, Ansible, Chef, CFEngine and Salt provide community contributed repositories to automate software installation, for example, Ansible Galaxy has 9329 roles available, Chef Supermarket has 3,135 cookbooks available although there are many duplicates. We call this is (automated) software deployment and building dynamic computing environments on virtual clusters is the main objective of this dissertation. Software defined systems (or virtual clusters) has discussed (Fox, 2013) to connect distributed big data and computing resources of Cloud and HPC, which will result in developing a suite of software deployment tools at scale. Note that this effort is mainly inspired by the previous research activities (Fox, Qiu, and Jha, 2014; Qiu et al., 2014; Fox and Chang, 2014; Fox et al., 2015; Fox et al., 2015; Fox et al., 2016).

2.2 Template

A template has been used to describe a deployment of software packages and infrastructure on virtual environments across multiple cloud providers because of its simple instructions as well as content shareability. YAML (superset of JSON) is a popular language to serialize data delivery especially as for configuration files and object persistence along with the template deployment. As an example of infrastructure deployments, Amazon Cloudformation, a template deployment service, uses YAML or JSON specification to describe a collection of Amazon virtual resources, Google Compute Cloud uses YAML with Jinja2 or Python languages to define a set of google compute resources whereas Microsoft Azure Resource Manager uses JSON to deploy Azure resources and Topology and Orchestration Specification for Cloud Applications (TOSCA) uses XML (Wettinger, Breitenbücher, and Leymann, 2014) to define a topology and a relationship. Saltstack and Ansible, a software deployment tool written in Python, use YAML to manage configuration and software installation from instructions defined in YAML text files.

Listing 1: AWS CloudFormation Example

```
Resources:
  EC2Instance:
    Type: AWS::EC2::Instance
    Properties:
      InstanceType:
        Ref: InstanceType
      SecurityGroups:
      - Ref: InstanceSecurityGroup
      KeyName:
        Ref: KeyName
```

The code example in Listing 1 is a plain text to deploy a Amazon EC2 instance written in a YAML format which includes a nested data structure by indentations and key value pairs for lists (starts with dash) and dictionaries.

Listing 2: Ansible Example

```
---
```

```
- hosts: opencv

  tasks:
  - name: compiler package
    apt: name=build-essential state=present update_cache=yes
  ...
```

Ansible, automation tool, uses YAML syntax with Jinja2 template to describe instructions of software installation and the code example in Listing 2 shows a code snippet of Ubuntu's APT (advanced packaging tool) installing build-essential Debian package during the OpenCV software installation.

There are several reasons to use a template for a deployment. First, installing software and building infrastructure typically demand lots of commands to run and additional configurations to setup and a template is suitable for these tasks with its data structures using key-value pairs, lists and dictionaries to contain all instructions to reproduce a same environment and to replicate an identical software installation on different locations at another time. In addition, with the advent of devops, a template deployment enables cooperation between a template developer and a template operator because a complicated set of resources and services is simplified by a single template file and delivered to an operator as an automated means of provisioning a same environment. Moreover, YAML or JSON is a simple text format for storing data which is easy to share and modify with anyone who interested in a template. There are still plenty of benefits that we can find when a template deployment is used.

Big Data applications typically require efforts on deploying all of the software prerequisites and preparing necessary compute resources. A template deployment reduced these efforts by offering an automated management on both tasks; software deployment and infrastructure provisioning, therefore we can focus on big data applications to develop.

The concept of serverless computing also applies to deploy applications with templates e.g. Listing 1. For instance, Amazon serverless compute, AWS Lambda, invokes serverless application code (also called function) based on the description of the template but uses a specific model e.g. Listing 3 for components of serverless applications. In detail, there is a main function (Handler), runtime environment (Runtime), and an actual code in a compressed format (CordUri).

Listing 3: AWS Serverless Application Model (SAM) Example

```
AWSTemplateFormatVersion: '2010-09-09'
Transform: 'AWS::Serverless-2016-10-31'
Resources:
  MyFunction:
    Type: 'AWS::Serverless::Function'
    Properties:
      Handler: hello_python.handler
      Runtime: python2.7
      CodeUri: 's3://my-bucket/function.zip'
```

2.3 Container technologies

Container technology has brought a lightweight virtualization with a Linux kernel support to enable a portable and reproducible environment across laptops and HPC systems. Container runtime toolkit such as Docker (Merkel, 2014), rkt (rkt, 2016) and LXD (lxd, 2016) has been offered since 2014 which uses an image file to initiate a container including necessary software packages and libraries without an hypervisor which creates an isolated environment using a virtual instance but with an isolated namespace on a same host operating system using the Linux kernel features such as namespaces, cgroups, seccomp, chroot and apparmor. Recent research (Felter et al., 2015) shows that containers outperform traditional virtual machine deployments yet running containers on HPC systems is still an undeveloped area. Shifter (Jacobsen and Canon, 2015) and Singularity (Kurtzer, 2016) have introduced to support containers on HPC with a portability and MPI support along with docker images. These efforts will be beneficial to scientific applications to conduct CPU or GPU intensive computations with easy access of container images. For example, a neuroimaging pipelines, BIDS Apps (Gorgolewski et al., 2016), is applied to HPCs using Singularity with existing 20 BIDS application images and Apache Spark on HPC

Cray systems (Chaimov et al., 2016) is demonstrated by National Energy Research Scientific Computing Center (NERSC) using shifter with a performance data of big data benchmark. Both researches indicate that scientific and big data workloads are supported by container technologies on HPC systems for reproducibility and portability.

Listing 4: Dockerfile Example

```
FROM ubuntu:14.04

MAINTAINER Hyungro Lee <lee212@indiana.edu>

RUN apt-get update && apt-get install -y build-essential
...
```

Dockerfile uses a custom template to describe installation steps of building docker images in a bash like simple format. There are certain directives to indicate particular objective of the commands, for example, FROM indicates a base image to use and RUN indicates actual commands to run.

2.4 Supporting scientific applications

With a rapid increase in the size of data sets and complexity of applications, research community considers accessibility, reproducibility, resource and data sharing (Grillner et al., 2016) on HPC systems and cloud computing to process large data sets with parallel and distributed frameworks on a set of compute nodes. Container technologies are now emerged (Hale et al., 2016) to enable large scale analysis with a minimum hassle on software deployments and infrastructure provisioning yet there are not many tools available to fully engage scientific application on containers efficiently. A small number of container images for scientific applications currently exist and most of the images are dedicated for a standalone mode which is not suitable for processing large data sets with serious computational workloads. Cluster deployments using containers are needed for big data applications which provide significant speedups with parallel job executions in either embarrassingly parallel or message passing interface. A number of scientific pipelines also require the support from the containers to enable reproducibility (Boettiger, 2015; Leipzig, 2016) in different platforms because most scientific pipelines have dependency issues from multiple software even in HPC systems with containers. Listing 5 shows a BLAST tool described by the Common Workflow Language Specification (CWL; `https://github.com/common-workflow-language`) which is for running a tool on a shared platform including cloud computing and Docker.

Listing 5: Common Workflow Language Specication (CWL) Example

```
cwlVersion: v1.0
class: CommandLineTool
requirements:
- $import: envvar-global.yml
- class: InlineJavascriptRequirement
- class: ShellCommandRequirement
- class: DockerRequirement
- $import: blast-docker.yml

inputs:
  db:
    type: String
    inputBinding:
      position: 1
    doc: BLAST database name
...
outputs:
  output:
  type: File
  outputBinding:
```

```
      glob: $(inputs.out)

baseCommand: blastn
```

3 Discussion

3.1 Problem: Ansible Roles in Building Compute Environments

Building compute environments needs to ensure reproducibility and constant deployment over time (Gil et al., 2007; Goodman et al., 2014). Most applications these days run with dependencies and setting up compute environments for these applications require to install exact version of software and configure systems with same options. Ansible is a DevOps tool and one of the main features is software deployment using a structured format, YAML syntax. Writing Ansible code is to describe action items in achieving desired end state, typically through an independent single unit. Ansible offers self-contained abstractions, named Roles, by assembling necessary variables, files and tasks in a single directory and an individual assignment (e.g., installing software A, configuring system B) is described as a role. Compute environments are usually supplied with several software packages and libraries and selectively combined roles conduct a software deployment where new systems require environments with needed software packages and libraries installed and configured. Although the comprehensive roles have instructions stacked with tasks to successfully finish a software deployment with dependencies, the execution of applications still need to be verified. In consequence, to preserve identical results from the re-execution of applications, it is necessary to determine whether environments are fit for the original applications. In certain situations, Ansible fails in building same environments due to following reasons. **First, a variety of operating systems and diverse source of packages are not able to construct equivalent environments across different platforms.** According to the Gnu/linux distribution timeline 12.10 (Lundqvist and Rodic, 2013), 480 linux distributions exist and each distribution has more than ten thousands packages e.g. Ubuntu Xenial 16.04 has 69154 and Debian Jessie 8 has 57062. Many Unix-like variant systems offer universal package manager e.g. apt on Debian, yum on CentOS, dnf on Fedora and pkg on FreeBSD to ease software installation, upgrading or removal through a central repository package (See details in Table 1). Ansible Conditionals can handle these multiple package managers with different package names e.g. Apache 2 is listed in RedHat as 'httpd' and in Debian as 'apache2' (see example Listing 6) but version differences are not considered. Table 2 shows that each distribution has different version of default packages therefore ansible roles may not install same version of packages when it is executed on various distributions. While most software packages are provided in official repositories, new and rapidly changing software are typically available from third-party repositories where reliability and security are not evaluated. In this situation, the re-executed results of application may differ across platforms although same input data and instructions are given. There are many factors that can cause this problem such as library versions, compiler options and dependencies but it is a difficult task to trace this low-level information and fix. **Second is conflicts (also known as software rot) among packages including existing software and libraries.** When Ansible runs towards target machines, software installation may fail due to conflicts between packages or with already installed software and libraries. For example, 25 CUDA packages for deep neural networks have dependencies and reverse dependencies (Figure 1). This may abort further installation or upgrade because of incompatibility issues and missing built-in rollback in Ansible makes failure handling more difficult. **Compile time is also inevitable** which takes a considerable amount of time to complete, especially when source code files are many and complex to compile. There are several techniques to minimize the compilation build time but the optimization is limited and CPU and memories are consumed by compilers.

Listing 6: Example of Apache Installation using Ansible Conditionals

```
- name: Apache Installation
  yum: name=httpd state=installed
  when: ansible_os_family == RedHat

- name: Apache Installation
  apt: name=apache2 state=installed
  when: ansible_os_family == Debian
```

Configuration drift, which creates divergent in server configuration makes building consistent and identical environments difficult as time goes on. In practice, software version and repository location may vary at install time although deployments are made from a same template. For instance, software provides a downloadable link to the latest release without a specific version in the link

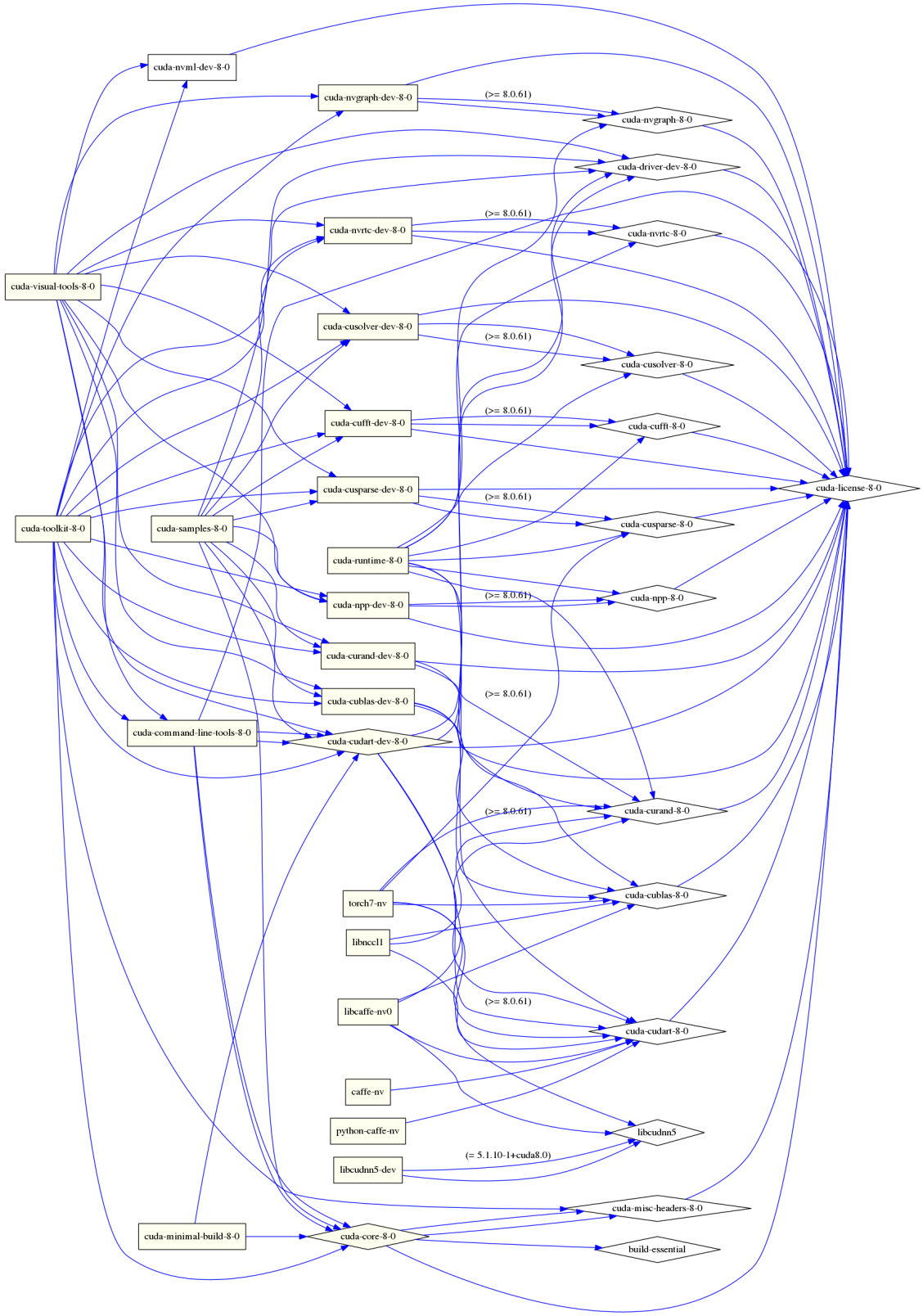
Name	Distribution	Package Type	file format	License	Language
dpkg	Debian	Binary	.deb	GPL	C, C++
apt	Ubuntu	Binary	.deb	GPL	C++
Nix	NixOS	Binary	.nix	LGPL	C++
RPM	RedHat	Binary	.rpm	GPL	C, Perl
dnf	Fedora	Binary	.rpm	GPL v2	C, Python
yum	CentOS	Binary	.rpm	GPL v2	Python
zypper	OpenSUSE	Binary	.rpm	GPL	C++
pacman	ArchLinux	Binary	.pkg.tar.xz	GPL v2	C
pkg	FreeBSD	Binary	.txz	GPL	C

Table 1: Package managers of Linux Distributions

Package	FreeBSD 11-STABLE	Debian 8.0 jessie	Ubuntu 16.04 LTS xenial	CentOS 7-1611	Fedora 25	openSUSE 42.2	Scientific Linux 7.3	NixOS 16.09
abiword(3.0.2)	3.0.1	3.0.0	–	–	–	3.0.1	–	3.0.1
alsa-lib(1.1.3)	1.1.2	1.0.28	1.1.0	1.1.1	1.1.1	1.1.2	1.1.1	1.1.1
ati-driver(16.40)	–	14.301.1001	–	–	–	–	–	–
bash(4.4)	4.4	4.3	4.3	4.2	4.3	4.3	4.2	4.3
bind(9.11.0-P3)	9.11.0-P3	9.9.5	9.10.3-P4	9.9.4	9.10.4-P3	9.9.9	9.9.4	9.10.4-P3
chromium(57.0.2987.110)	57.0.2987.110	41.0.2272.118	–	–	–	–	–	53.0.2785.116
cups(2.2.2)	2.2.2	1.7.5	2.1.3	1.6.3	2.2.0	1.7.5	1.6.3	2.1.4
dhcp(4.3.5)	4.3.5	4.3.1	4.3.3	4.2.5	4.3.5	4.3.3	4.2.5	4.3.4
e2fsprogs(1.43.4)	1.43.4	1.42.12	1.42.13	1.42.9	1.42.13	1.42.11	1.42.9	1.42.13
firefox(52.0.1)	52.0.2	31.6.0	45.0.2	45.4.0	49	49.0.2	45.4.0	49
freetype(2.7.1)	2.7.1	2.5.2	2.6.1	2.4.11	2.6.5	2.6.3	2.4.11	2.6.5
gcc(6.3.0)	5.4.0	4.9.2	5.3.1	4.8.5	6.2.1	4.8	4.8.5	5.4.0
gimp(2.8.20)	2.8.18	2.8.14	–	2.8.16	–	2.8.18	2.8.16	2.8.18
glibc(2.25)	–	2.19	2.23	2.17	2.24	2.22	2.17	2.24
gnome-shell(3.24.0)	3.18.4	3.14.2	–	3.14.4	3.22.1	3.20.4	3.14.4	3.20.3
gnucash(2.6.16)	2.6.15	2.6.4	–	–	–	–	–	2.4.15
gnumeric(1.12.34)	1.12.28	1.12.18	–	–	–	–	–	1.12.32
grub(2.00)	2	2.02beta2	2.02beta2	2.02beta	2.02beta	2.02beta2	2.02beta	0.97
gtk+(3.22.11)	3.18.8	3.14.5	3.18.9	3.14.13	3.22.2	3.20.9	3.14.13	3.20.9
httpd(2.4.25)	2.4.25	2.4.10	2.4.18	2.4.6	2.4.23	2.4.23	2.4.6	2.2.31
inkscape(0.92.1)	0.92.0	0.48.5	–	0.91	–	0.91	0.91	0.91
k3b(2.0.3a)	2.0.3	2.0.2	–	2.0.2	–	2.0.3	2.0.2	2.0.3a
kmod(24)	–	18	22	20	23	17	20	23
libgnome(2.32.1)	2.32.0	2.32.1	–	2.32.1	–	2.32.1	2.32.1	2.32.1
libreoffice(5.3.1)	5.2.5	4.3.3	5.1.2	5.0.6	5.2.3	5.1.5.2	5.0.6	5.1.5
linux(4.10.6)	–	3.16.7	4.4	3.1	4.8.6	4.4.27	3.1	4.4.23

Table 2: 26 major package versions of eight Linux Distributions (BODNAR, 2013)
(where most common versions are Green and the latest version is Blue)

Figure 1: Example of Package Dependencies for CUDA Libraries (1-level depth)



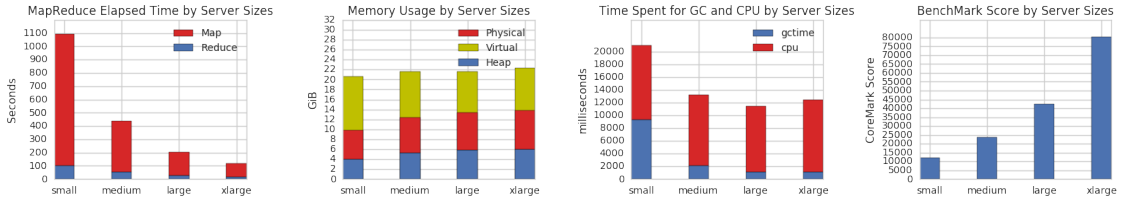


Figure 2: Hadoop Comparison by Server Sizes
(where small has 1vCPU and 2GiB memories, medium has 2vCPUs and 4GiB, large has 4vCPUs and 8GiB and xlarge has 8vCPUs and 16GiB. GC stands for a garbage collection.)

therefore an unique link is used to download. However, if a link to the latest release is defined in scripts to download software package, an actual version of the release may not be same when software downloading occurred at a different time, especially where frequent releases are applied to software development. This will increase the likelihood of building another environments or getting failure of deployment.

In addition, **provisioning proper computing resources for an application is not feasible** because virtual server provisioning by Ansible is not bound by the application deployment. Decoupled infrastructure and applications may cause an execution failure of the applications or poor performance due to insufficient compute resources. Applications deployed on virtual environments need to run with particular computing resources such as GPU support, InfiniteBand options, and Solid State Drive (SSD) with TRIM support to satisfy performance requirements and ensure same results. Figure 2 shows that a linear performance increment from small to xlarge instance type for Hadoop and the garbage collection overhead is observed in the small instance type. Ansible Roles are tailored to application deployment but it is not for allocating proper hardware resources. Manual provisioning plans are necessary to meet the application requirements. **Vendor lock-in problem in deploying Ansible roles prevents building a same environment across multiple cloud providers** although Ansible provides multi-cloud functions (called modules in Ansible) to favor portability and agility. For example, Amazon CloudFormation, Google Compute Instance Templates, Microsoft Azure Templates and OpenStack Heat have an individual specification that defines properties and resources of the infrastructure. Inter-cloud standard specification needs to be defined, thereby building a similar environment with vendor free templates. **Software deployment using Ansible may not work in the HPC clusters due to the restriction of root or superuser privileges which Ansible invokes package managers e.g. apt-get, yum, dnf or pkg with sudo command**. As a workaround, many HPC systems provide a user environment by modules, the software environment management, or virtualenv, the isolated directory for Python or RVM for Ruby but system software packages still need admin privileges to setup required libraries and software globally.

The following approaches are suggested to address these issues: integration Ansible with Linux Container, performance roles with the best server size, application-centric deployment, deployment optimization with package dependency graph, building environments on HPC with containers, and code analysis for preparing domain specific dependencies.

3.1.1 Approach: Containerizing Software Deployment

Container image comprises a stack of filesystem layers to build compute environments at a operating-system-level virtualization. Docker, for example, creates a container image by stacking up layers of containers to represent a root filesystem when Docker launches an instance of the image. Therefore the required software, libraries and configurations are preserved like virtual machine images but in a lighter way. Union filesystem such as aufs or overlayFS enables a single logical filesystem using merged contents i.e. files and directories and no duplicates. Also, Docker takes the DevOps principal to provide transparency of building images in a script i.e. Dockerfile, therefore the blue print of containers is explained with actual commands to show what is inside of the image (Boettiger, 2015). If a custom build is necessary for an improvement or a repair of a bug, this script is useful to update the image. A container image provides an identical environment over time but new images need to be generated manually when software updates or bug fixes are applied to images. Versioning images helps to choose an

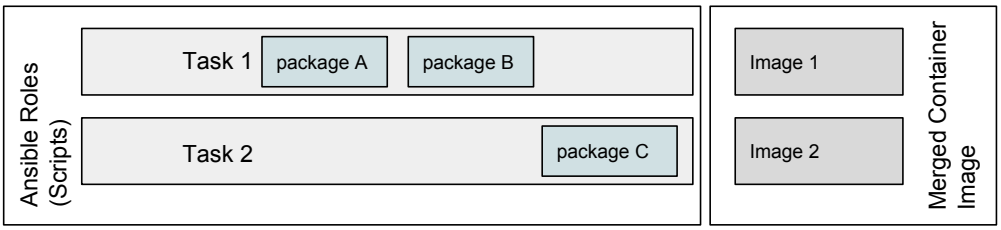


Figure 3: Creating Container Images from Ansible Roles

```
ee7...e9e (unionFS unique ID for nano)
├─ bin
│   ├─ nano
│   └─ rnano -> nano
└─ etc
    ├─ nanorc
    └─ alternatives
        ├─ editor -> /bin/nano
        ├─ editor.1.gz -> /usr/share/man/man1/nano.1.gz
        ├─ pico -> /bin/nano
        └─ pico.1.gz -> /usr/share/man/man1/nano.1.gz
```

Figure 4: Directory Tree for Nano Editor Program

specific image with changes made to environments. On the other hand, Ansible roles build environments at the execution time which means that latest software updates and bug fixes are applied when it is being run. Tasks in the roles which perform software installation and configuration simplify entire process of building environments but preserving a same environment is not guaranteed unless specific versions of all software packages are preserved. Continuous integration tools e.g. Travis or Jenkins are provided to evaluate equivalence between two environments. We propose **containerizing Ansible Roles to deliver a same environment with deployed software packages via container images** (Figure 3). The use of container images has advantages such as consistency, simplicity and saving of storage due to a stackable file system. For example, an individual image contains installed software files with a directory structure (Nano Editor in Figure 4) and multiple images can be merged to build a final environment. In addition, **cloud-init, the initialization script of virtual machines can be invoked** to run Ansible roles thereby applying recent changes. The image of containers is stored and used for the container runtime e.g. docker, and cloud-init is called after a booting process, in this case, Ansible roles will be executed to accomplish particular tasks such as software update or bug fixes. This combination ensures building equivalent compute environments with the latest security patches for vulnerable software, if any. Snapshot images with versions are still viable to restore environments if the execution of applications with recent changes is failed or irreproducible.

3.1.2 Approach: Deploying Best Performance Roles with Server Size Recommendation

Paired roles and infrastructure provisioning contain a set of activities to fulfill a perspective in application deployments of roles along with compute resources. In simple terms, hardware will be tailored to

Provider	Instance Type	vCPUs	Memory	Network (Mbits/sec)	Storage Bandwidth (MBs/sec)	Score - Single	Score - Multi
aws	t2.micro	1 cores	1.0 GB	300	62.5	2549	2541
aws	t1.micro	1 cores	0.613 GB	200	62.5	1046	1325
aws	t2.small	1 cores	2.0 GB	300	62.5	2477	2466
aws	m1.small	1 cores	1.7 GB	300	62.5	771	763
aws	t2.medium	2 cores	4.0 GB	300	62.5	2626	5129
aws	m3.medium	1 cores	3.75 GB	300	62.5	1333	1299
aws	m1.medium	1 cores	3.75 GB	300	62.5	1472	1467
aws	c3.large	2 cores	3.75 GB	500	62.5	2527	3016
aws	c4.large	2 cores	3.75 GB	1000	62.5	3326	3911
aws	t2.large	2 cores	8.0 GB	300	62.5	2986	5676
aws	c1.medium	2 cores	1.7 GB	300	62.5		3307
aws	m4.large	2 cores	8.0 GB	1000	56.25	2869	3346
aws	m3.large	2 cores	7.5 GB	300	62.5	2579	3034
aws	r3.large	2 cores	15.25 GB	1000	62.5	2675	3143
aws	m1.large	2 cores	7.5 GB	300	62.5	1592	3106
aws	c3.xlarge	4 cores	7.5 GB	500	62.5	2866	6620
aws	c4.xlarge	4 cores	7.5 GB	1000	93.75	3402	7807
aws	m2.xlarge	2 cores	17.1 GB	300	62.5	4485	4485
aws	m4.xlarge	4 cores	16.0 GB	1000	93.75	2772	6103
aws	m3.xlarge	4 cores	15.0 GB	300	62.5	2237	4894
aws	r3.xlarge	4 cores	30.5 GB	1000	62.5	2542	5958
aws	m1.xlarge	4 cores	15.0 GB	300	62.5	1560	5428
aws	c3.2xlarge	8 cores	15.0 GB	1000	125	2607	11327
aws	c4.2xlarge	8 cores	15.0 GB	1000	125	3255	13408
aws	m2.2xlarge	4 cores	34.2 GB	300	62.5		6563

Table 3: Benchmark Score for AWS EC2 Instances by GeekBench

the system requirements of application deployments. Infrastructure provisioning is expected to deploy virtual machines with suitable compute resources for the roles prior to the deployments therefore expectations for infrastructure and platform layers meet in terms of computing performance and resource utilization as well as reproducibility (Santana-Perez and Pérez-Hernández, 2015; Nekrutenko and Taylor, 2012). Templates (also called IaaC - Infrastructure as a Code) are the best fit to automate infrastructure provisioning in this context because templates written in JSON or YAML are easily programmable in accordance with application deployments. Server types with preferred CPU cores, storage options, and memory sizes are mainly considered to engage performance and utilization efficiently and additional resources can be attached to satisfy individual needs regarding to building custom infrastructure. First plan is **pairing roles and infrastructure with a server size recommendation**. Listings of infrastructure templates are provided to browse and the developers quickly find desired resource groups for the application deployment. Listing 7 shows a preliminary model of the integration which eliminates details of infrastructure provisioning but defines a minimal computing power to ensure expected performance for the application. The roles for software A and B are deployable with the default infrastructure "medium" and other options are allowed to choose as an alternative. The hardware details are described in separate templates with certain hardware components, supported providers and machine types accommodating the requirements. The abstraction of infrastructure (Listing 8) aims to reduce vendor lock-in issues by grouping items based on similar properties e.g. number of CPU cores, memory size or disk size and provider templates (Listing 9) exist beneath it for actual provisioning and configuration. The next phase is **deploying roles through community developed infrastructure**. For example, Microsoft Azure QuickStart Templates provides more than 400 templates to build infrastructure and Simple Azure Python library provides an interface to search relevant templates with a search keyword of software name or particular resource type. The last phase is **offering an infrastructure by tool profiling** (Chard et al., 2016) or **suggesting runtime environments with containers using automated infrastructure provisioning** (Yamato, 2016). To find an optimal computing performance from various cloud server types, benchmark scores can be used as a requirement of server provisioning. For example, Amazon EC2 has 57 instance types with 13 sub-groups, Google Compute Engine provides 21 instance types with 4 sub-groups and Microsoft Azure offers 51 instance types with 7 sub groups (A, D, F, G, H, L, and N types) with different combinations of CPUs, memories, storage and networks. CPU Benchmark score e.g LINPACK, SPECInt, UnixBench, GeekBench, or CoreMark can be used instead of specifying a particular server types when virtual instances are launched.

Listing 7: Prototype of Infrastructure Provisioning with Benchmark Score(Table 3)

```
systems:
  roles:
    - software A
    - software B
    - ...
  infrastructure:
    cpu-performance:
      - geekbench:=>5000
      - medium
```

Listing 8: Medium Server Template for Multi Cloud Platforms

```
requirement:
  - cpu: 2
  - mem: 8gb
  - disk: 20gb
provider:
  default: aws
  options:
    - gce
    - openstack
    - azure
template:
  aws: aws-medium.yml
  gce: gce-medium.yml
  openstack: openstack-medium.yml
  azure: azure-medium.yml
machine_code:
  aws:
    - m4.large
  gce:
    - n1-standard-2
  azure:
    - Standard_D2
    - Standard_A5
    - Standard_A2m_v2
  openstack:
    - m1.large
```

Listing 9: Server Provisioning on OpenStack Heat (openstack-medium.yml from Listing 8)

```
heat_template_version: 2013-05-23
...(omitted)...
resources:
  scaling:
    type: OS::Heat::ResourceGroup
    properties:
      resource_def:
        type: OS::Nova::Server
        properties:
          flavor: { get_param: machine_code }
```

3.1.3 Approach: Application Centric Deployment

Ansible roles are designed to install, configure and manage a software package but applications need be deployed by combining multiple ansible roles. This may require manual patches to fix conflicts from the

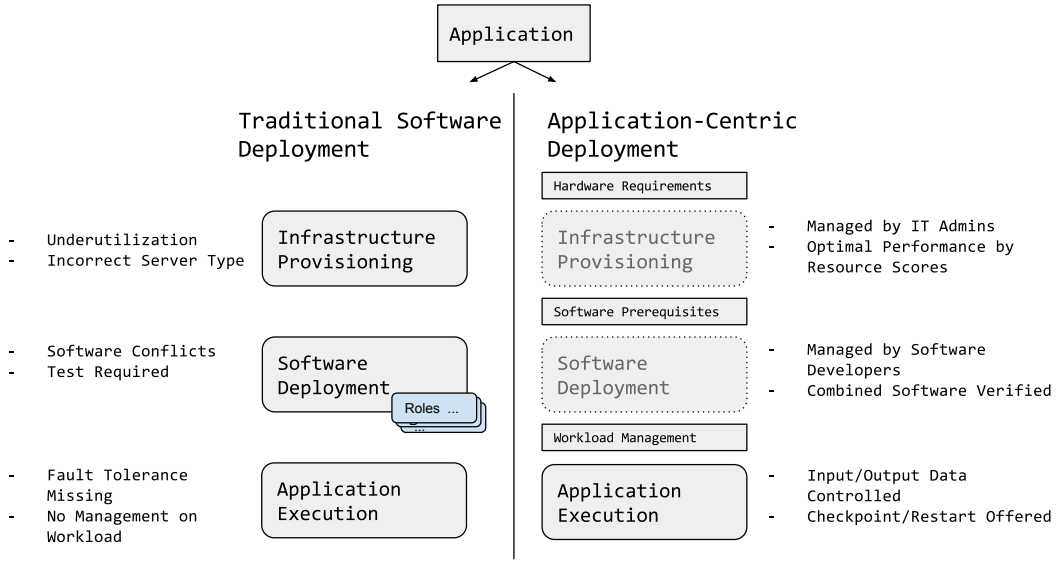


Figure 5: Procedure Comparison between Traditional Deployment and App-Centric Deployment

merge or rewriting whole ansible roles are necessary to achieve an application deployment on various platforms. Application-centric deployment (ACD) aims to build a compute environment focusing on an application without dealing with details of infrastructure provisioning and software conflicts. ACD describes input and output data of an application with its state rather than managing hardware specifications and software versions although requirements of them need to be declared for a deployment. The actual execution and workload of an application is the most important in ACD, therefore application efficiency is ensured with proper amount of computing resources e.g. number of virtual CPU cores, size of memories and network bandwidth. There are certain benefits we can expect from ACD compared to the traditional software-focused deployment e.g. Ansible :

- **Agility:** ACD abstracts underlying hardware requirements and infrastructure setups across different cloud providers. A standardized instruction provides flexibility against various linux distributions.
- **Cost Efficiency:** Minimal resource underutilization is expected by suggesting proper server types and adopting container technologies.
- **Simplicity:** Separation from preparing software and platforms allows application developers to meet application requirements such as performance and resilience and avoid a such complexity.

The goal of this approach are reducing the problem of offering proper computing resources for an application. The conceptual procedure is depicted in Figure 5.

3.1.4 Approach: Optimizing Software Deployment Using Package Dependency Map

Open source software packages have several dependencies especially if the packages are large and complex. These dependencies are typically libraries and tools that are required for installing and running an application. For example, web server software needs libraries for parsing, encoding, securing, and visualizing as well as many other tasks of web services. Sometimes it is better to understand there are possibilities of duplicates and conflicts among software dependencies. Building dependency graph may offer efficiencies in deploying software packages by extracting necessary libraries from import modules of the source code along with the package metadata e.g. pom.xml and setup.py and descriptions e.g. README. This approach will provide a giant structural view of the relation between software, dependencies, description and relevant data. Visualization is not a main purpose of this approach, collecting statistical data of dependency information is more emphasized to highlight dependencies with usage and relevance according to functionality of applications.

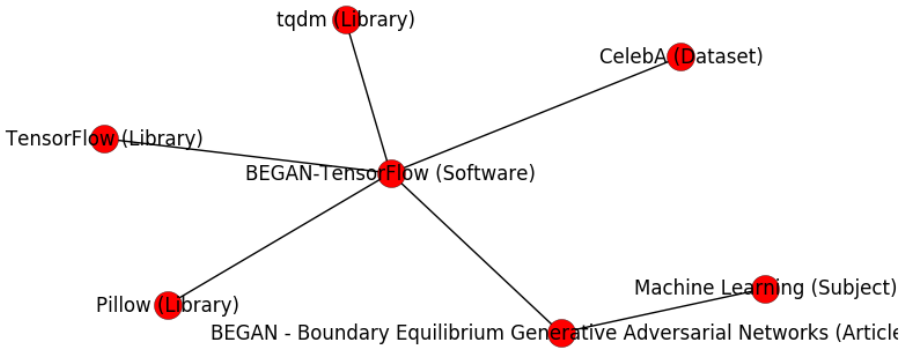


Figure 6: Dependency Map Example for Tensorflow Implementation of "BEGAN: Boundary Equilibrium Generative Adversarial Networks" (Berthelot, Schumm, and Metz, 2017)

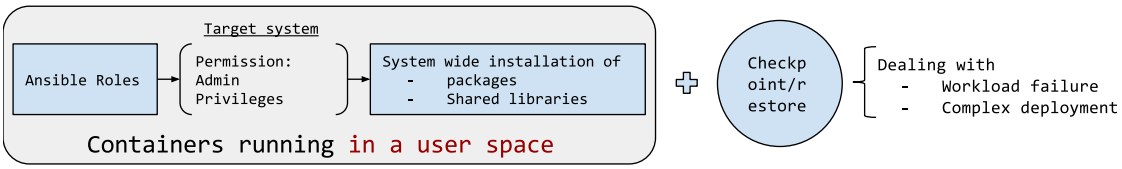


Figure 7: Containers enclosing Ansible Roles

3.1.5 Approach: Building Individual Environments on HPC using Unprivileged Containers

From the user's perspective, Ansible roles for software deployment on high performance computing (HPC) systems is infeasible because administrative support (superuser privileges) is required to complete all tasks defined in the roles such as installing shared libraries and handling dependencies in a shared space of a multi-user system. The researches (Gamblin et al., 2015; Geimer, Hoste, and McLay, 2014; Devresse, Delalondre, and Schürmann, 2015) indicate the difficulty of software management on HPC due to this reason and propose various tools to resolve such a hassle. Linux containers, with the benefits of a union file system, i.e. Copy-on-write (COW) and a namespace isolation, allow users to have a personal environment by a container image with required libraries and software installed, therefore the manual effort of preparing compute environments on HPC also can be diminished (Kurtzer, 2016; Jacobsen and Canon, 2015; Priedhorsky and Randles, 2016). In this approach, Ansible roles will be converted to container scripts and then container runtime tools on HPC e.g. Singularity, Shifter and chroot import the container images (generated from the scripts) to provide a same runtime environment on HPC as one on other platforms. In addition to that, fault tolerance is supported for complex deployment and distributed workload on HPC. Checkpoint/restore in a userspace (CRIU) is available for containers i.e. Docker to preserve workload and prevent any loss from the failure in enormous systems. **The template that we described earlier for a software deployment will be expanded to capture the building information of a container image on HPC and the conversion**. Another benefit from this approach is a portability in different platforms because all required libraries and programs are included and retrieved from a container image running in a user space with unprivileged mode (See Figure 7). The generalized abstraction on how to convert between ansible roles and container scripts will be defined in the template specification therefore same functionality of the roles can be ensured through containers.

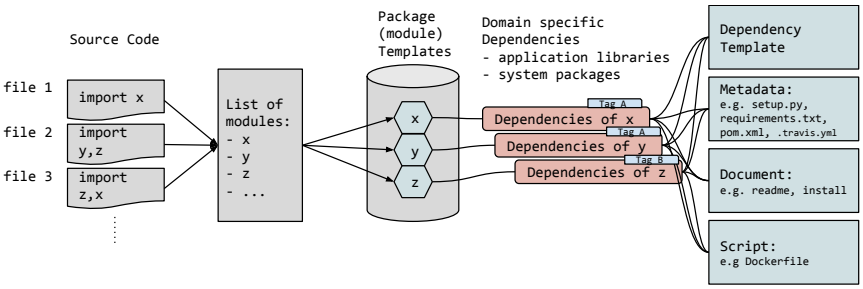


Figure 8: Overview of Managing Software Dependencies by Code Analysis

3.1.6 Approach: Automated Dependency Manager for Domain Specific Software

The goal of this approach is preparing compute environments on the premises where domain-specific applications run on Function as a Service (FaaS). Amazon Lambda, Google Functions, Microsoft Azure Functions and IBM OpenWhisk offer an interface to run code without building servers but the supported languages are limited as Javascript, C, Python and Java and the policy of preparing development environments is 'bring-your-own-environment' (BYOE). In addition, automated infrastructure provisioning for these services does not offer best performance because cost efficiency is mainly considered by using inexpensive and less reliable server types e.g. AWS spot instances. To reduce complexity of composing environments but with powerful computing resources, an analysis tool is introduced i.e. Simple Azure for Microsoft Azure Resource Manager Templates, in demonstrating a concept of automated server provisioning with a choice of domain specific environments. Application deployment templates contain dependency information to construct suitable environments and identify requirements of building proper compute resources to present better performance in computation and data processing compared to existing services e.g. Azure Functions. In Python, for example, module names (package) are defined in source code regardless of internal or external modules. When a user submits code to run on FaaS, the `import` functions are analyzed to obtain dependency information from the package templates where all dependencies are described for the modules defined in the `import` (See Figure 8).

4 Template Deployment and Orchestration

Template deployment is a means of installing software and building infrastructure by reading a file written in a templating language such as YAML, JSON, Jinja2 or Python. The goal of a template deployment is to offer easy installation, repeatable configuration, shareability of instructions for software and infrastructure on various platforms and operating systems. A template engine or an invoke tool is to read a template and run actions defined in a template towards target machines. Actions such as installing software package and setting configurations are described in a template file using its own syntax. For example, YAML uses spaces as indentation to describe a depth of a dataset along with a dash as a list and a key-value pair with a colon as a dictionary and JSON uses a curly bracket to enclose various data types such as number, string, boolean, list, dictionary and null. In a DevOps environment, the separation between a template writing and an execution helps Continuous Integration (CI) because a software developer writes deployment instructions in a template file while a system operations professional executes the template as a cooperative effort. Ansible, SaltStack, Chef or Puppet is one of popular tools to install software using its own templating language. Common features for those tools are installing and configuring software based on definitions but with different strategies and frameworks. One observation is that the choice of implementation languages for those tools influences the use of a template language. The tools written by Python such as Ansible and SaltStack use YAML and Jinja which are friendly to a Python language with its library support whereas the tools written by Ruby such as Chef and Puppet use Embedded Ruby (ERB) templating language. In scientific community, a template has been used to describe data and processes of pipelines and workflow because a template contains detailed information of them in writing and assists sharing and connecting between different layers and tools. Parallel execution on distributed environments is also supported in many tools yet enabling computations in a scalable manner needs expertise to prepare and build the environments. We propose a template orchestration to encourage scientists in using distributed compute resources from HPC and cloud computing systems in which provisioning infrastructure is documented in a template and complicated pipelines and workflows are packaged by container technologies for reproducibility.

4.1 Template deployment for Big Data Applications

Software installations and configurations for particular domains have become hard to maintain because of an increased number of software packages and complexity of configurations between them to connect. Template deployment for installing and provisioning systems across from a single machine to large number of compute nodes is proposed to achieve consistent and reliable software deployment and system provisioning.

First, we plan to implement a deployment tool with default components for big data software such as Apache Hadoop, Spark, Storm, Zookeeper, etc. therefore a software deployment can be achieved by loading existing templates instead of starting from scratch. The software deployment intends to support various linux distribution with different versions, therefore the software stacks are operational state in many environments without a failure.

Listing 10: Template Deployment for Big Data

```
stacks:
  - software A
  - software B
  - ...
```

Each item i.e. software indicates a single template file to look up deployment instructions. Dependencies indicates that related items to complete a deployment and the environment variables are shared while dependencies are deployed. If container image is available on the web, container image deployment is expected using the URI location to save compile time.

Listing 11: Sample of software template

```
instruction:
  - install package A
  - download data B
```

```
location:
  <URI>
dependency:
  - software A
  - library B
environment_variables:
  - HOME_DIR=/opt/software_a
```

Infrastructure deployment is provisioning of cloud computing which includes virtual machine images, server types, network groups, etc. in preparation of virtual resources for the software stacks. Infrastructure deployment for multiple cloud platforms includes Microsoft Azure Resource Manager Templates, Amazon CloudFormation Templates, and Google Compute Instance Templates. Each cloud provider owns individual models for their services therefore a template of the deployment is solely executable in each provider although similar infrastructure is necessary for the software stacks.

Listing 12: Support for cloud providers

```
infrastructure:
  - default: aws
  - options:
    - aws
    - gce
    - azure
    - openstack
aws:
  services:
    image:
      - image A
      - image B
      - image B version 2
    server:
      - server type A
    network:
      - network interface a
      - network ip address a
```

We plan to integrate container based deployments with popular tools such as Docker therefore image based software deployment is also supported to enhance reproducibility and mobility on different environments.

Listing 13: Template Deployment with Containers

```
format:
  - default: docker
  - options:
    - docker
    - ansible
    - shell
    - rkt
```

Template has been used to document instructions for particular tasks such as software installation and configuration or infrastructure provisioning on cloud computing, however, shareability of templates is not improved which requires for better productivity and reusability. We plan to design a template hub to collect, share, search and reuse well written templates with a common language e.g. yaml or json, therefore building software stacks and provisioning infrastructure both are repeatable in any place at any time.

In addition, provenance data and process state will be reserved.

4.2 Infrastructure Provisioning on Clouds

Infrastructure provisioning has supported with templates in many cloud platforms i.e. Amazon Cloudformation, Microsoft Azure Resource Manager, OpenStack Heat and Google Compute Instance Templates. Infrastructure described in a template will be created for simple tasks running in a standalone machine or multiple tasks in clusters.

4.2.1 Simple Azure - Python Library for Template Deployment on Windows Azure

Implementation of infrastructure provisioning is provided with Azure use case. Simple Azure is a Python library for deploying Microsoft Azure Services using a Template. Your application is deployed on Microsoft Azure infrastructure by Azure Resource Manager (ARM) Templates which provides a way of building environments for your software stacks on Microsoft Azure cloud platform. Simple Azure includes 407 community templates from Azure QuickStart Templates to deploy software and infrastructure ranging from a simple linux VM deployment (i.e. 101-vm-simple-linux) to Azure Container Service cluster with a DC/OS orchestrator (i.e. 101-acs-dcos). It supports to import, export, search, modify, review and deploy these templates using the Simple Azure library and retrieve information about deployed services in resource groups. Initial scripts or automation tools can be triggered after a completion of deployements therefore your software stacks and applications are installed and configured to run your jobs or start your services. Starting a single Linux VM with SSH key from Azure QuickStart Template is described in listing 14:

Listing 14: Simple Azure

```
>>> from simpleazure import SimpleAzure
>>> saz = SimpleAzure()

# aqst is for Azure QuickStart Templates
>>> vm_sshkey_template = saz.aqst.get_template('101-vm-sshkey')

# arm is for Azure Resource Manager
>>> saz.arm.set_template(vm_sshkey_template)
>>> saz.arm.set_parameter("sshKeyData", "ssh-rsa AAAB... hrlee@quickstart")
>>> saz.arm.deploy()
```

4.3 Semantics

Advances in big data ecosystem will require to connect scattered data sources, applications and software in meaningful semantics. It is necessary to develop structured semantics as an effort of support in discovering big data tools, datasets and applications all connected because semantics is more understandable to both human and machine with a standard syntax for expressing contents in RDF (Resource Description Framework) model or JSON-LD (Linked Data using JSON) (Labrinidis and Jagadish, 2012; Bizer et al., 2012; Simmhan et al., 2013). It also provides a guideline to construct big data software stacks to community in which preparing development environments is complicated with newly introduced software and datasets. This is particularly useful given the increasing number of tools, libraries and packages for further development of big data software stacks. One example in the listing 15 shows two applications, C++ Parser for MNIST Dataset and a Python package to convert IDX file format provided by Yann LeCun's dataset, are available for MNIST database of handwritten digits on github. There are couple of tasks to implement semantics for template deployment:

1. collect big data software, applications, and datasets
2. produce JSON-LD documents
3. derive Rest API to search, list and register
4. implement a library to explore documents about big data ecosystem

Listing 15: Sample of linked data between dataset and software

```
{
    "@context": "http://schema.org/",
    "@type": "Dataset",
    "distribution": "http://yann.lecun.com/exdb/mnist/",
    "workExample": [
      {
        "@type": "SoftwareSourceCode",
        "codeRepository": "https://github.com/ht4n/CPPMNISTParser",
        "description": "C++ Parser for MNIST Dataset",
        "dateModified": "Sep 1, 2014",
        "programmingLanguage": "C++"
      },
      {
        "@type": "SoftwareSourceCode",
        "codeRepository": "https://github.com/ivanyu/idx2numpy",
        "description": "A Python package which provides tools to convert
           files to and from IDX format",
        "dateModified": "Sep 16, 2016",
        "programmingLanguage": "Python"
      }
    ]
  }
```

5 Container Technology

With the increased attention of Docker container software and reproducibility, the use of virtualization has been moved from the hypervisor to a linux container technology which shares kernel features but in a separated name space on a host machine with a near native performance (Felter et al., 2015). The recent researches (Benedicic et al., 2016) indicate that the HPC community takes account of container technologies to engage scientists in solving domain problems with less complication of deploying workflows or pipelines on multiple nodes as new implementations have been introduced (Kurtzer, 2016; Jacobsen and Canon, 2015; Priedhorsky and Randles, 2016). Container technology with HPC, however, is focused on supporting compute-intensive applications i.e. Message Passing Interface (MPI) although many scientific problems are evaluated with big data software and applications. Investigation on container technology with big data ecosystem is necessary to nurture the data-intensive software development on HPC with a rich set of data analysis applications.

Modern container software run with container images to create isolated user space based on pre-configured environments. Authoring container image definition is a first step to prepare custom environments via containers and to share with others. Dockerfile is a text file to create a docker container image with instructions for package installation, command executions, and environment variable settings. Definition File of Singularity also contains similar instructions to build container images. Application Container Image (ACI) of CoreOS rkt is generated by a shell script and acbuild command line tool but building container images is similar to docker. The main objective of using these container image definitions (formats?) is to reveal user commands and settings explicitly therefore the development environment can be shared easily and conversion between other platforms is doable. The initial goal of using container technology in this dissertation is building a container-based big data ecosystem by offering a template-based deployment for container images. It would also enable a concise and descriptive way to launch complex and sophisticated scientific pipelines using existing container images or deployment scripts. Performance tests are followed to demonstrate efficiency of the deployments with big data applications on modern container technologies. We desire to measure overhead introduced by container software i.e. shifter, singularity on HPC environments with comparison of CPU, memory, filesystem, and network usages.

Template based deployment is adopted in container technologies, for example, Singularity uses a custom syntax, SpecFile to describe the creation of a container image with directives which are similar to Dockerfile. Listing 16 shows an example of Caffe Deep Learning Framework Singularity image creation.

Listing 16: Singularity Example

```
DistType "debian"
MirrorURL "http://us.archive.ubuntu.com/ubuntu/"
OSVersion "trusty"

Setup
Bootstrap

...(suppressed)...
RunCmd git clone -b master --depth 1 https://github.com/BVLC/caffe.git
RunCmd sh -c "cd caffe && mkdir build && cd build && cmake -DCPU_ONLY=1 ..."
RunCmd sh -c "cd caffe/build && make -j1"

RunCmd ln -s /caffe /opt/caffe
RunScript python
```

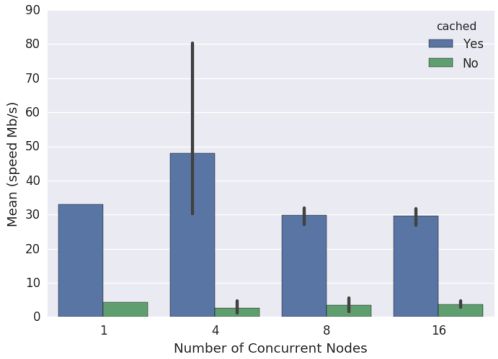
5.1 Common Installed Packages

One of the benefits of using template deployment is that a list of installed software packages is included in the instruction, therefore common packages are revealed for particular collections. Table 4 is an example of debian packages described in Dockerfiles related to NIST collection and dpkg, debian package command, has been used to collect package information.

Name	Description	Dependencies	Size (Kb)	Priority
build-essential	Informational list of build-essential packages	dpkg-dev, libc6-dev, gcc, g++, make	20 (14464)	optional
python-dev	header files and a static library for Python (default)	python, python2.7-dev, libpython-dev	45 (1024)	optional
autoconf	automatic configure script builder	m4, debianutils, perl	1890 (17956)	optional
software-properties-common	manage the repositories that you install software from (common)	python3-dbus, python-apt-common, python3-software-properties, gir1.2-glib-2.0, ca-certificates, python3:any, python3-gi, python3	184 (3125)	optional
python	interactive high-level object-oriented language (default version)	libpython-stdlib, python2.7	680 (384)	standard
automake	Tool for generating GNU Standards-compliant Makefiles	autoconf, autotools-dev	1484 (2074)	optional
zlib1g-dev	compression library - development	libc6-dev, zlib1g	416 (12516)	optional
apt-utils	package management related utility programs	libgcc1, libapt-inst1.7, libstdc++6, apt, libdb5.3, libc6, libapt-pkg4.16	688 (21070)	important
g++	GNU C++ compiler	cpp, gcc, g++-5, gcc-5	16 (51922)	optional
binutils	GNU assembler, linker and binary utilities	zlib1g, libc6	12728 (10924)	optional
gcc	GNU C compiler	cpp, gcc-5	44 (22199)	optional
python-numpy	Numerical Python adds a fast array facility to the Python language	python, python2.7:any, libblas3, liblapack3, libc6	8667 (17873)	optional
nodejs	evented I/O for V8 javascript	libssl1.0.0, libc6, libstdc++6, zlib1g, libv8-3.14.5, libc-ares2	3043 (20625)	extra
pkg-config	manage compile and link flags for libraries	libglib2.0-0, dpkg-dev, libc6	140 (17322)	optional
python-imaging	Python Imaging Library compatibility layer	python-pil, python:any	45 (1248)	optional

Table 4: Top 15 Debian-based Packages used in Dockerfiles for the NIST collection on Github, size with parenthesis indicates total size including dependency packages

Figure 9: Accelerated Common Package Installation using Software Package Proxy



Type	Hits	Misses	Total
Requests	104993 (95.26%)	5220 (4.74%)	110213
Data	12627.32 MiB (99.78%)	27.95 MiB(0.22%)	12655.27 MiB

Table 5: Cache Efficiency for Software Package Installation measured by apt-cacher-ng

5.2 Evaluation

As a part of dissertation, performance tests of container technologies with big data applications from NIST Collection. There are six applications in the collection: Fingerprint Matching, Human and Face Detection, Twitter Live Analysis, Data Warehousing, Healthcare Information, and Geospatial information. Performance data on CPU, memory, storage and network will be measured on HPC and cloud computing with container software i.e. docker, rkt, singularity and shifter.

Preloading common packages shows possible optimization for the template deployment according to the figure 9. With a considerable reduce on network traffic for downloading packages, 10x speedup is approximately observed over multiple access to Debian software package mirror sites. Statistics for the cache reuse (Table 5) indicates that the most benefit of the speedup is gained from the cached packages. In addition, standard deviation for download speed is higher in using remote mirrors than cached proxy server in which network consistency and reliability are ensured with low standard deviation for download speed.

5.3 Docker Terminologies

- **aufs** is Advanced multi-layered Unification FileSystem which implements a union mount for Linux file systems
- **Container** is an isolated userspace created in operating-system-level virtualization
- **COW** Copy-On-Write is a resource management technique to share the original over multiple copies
- **CRIU** is a fault tolerant technique to provide checkpoint and restore in userspace
- **Docker** is an implementation of operating-system-level virtualization using kernel features and union mount filesystems
- **Dockerfile** is a plain text file that contains instructions to build a new image, and Dockerfile is similar to scripts but provides commands with Docker Directives
- **Layer** in a union mount filesystem, each layer is a change instructed by Dockerfile.
- **overlayfs** is a overlay filesystem which is the result over overlaying one filesystem on top of the other, and overlayfs is supported in the upstream mainline Linux kernel

6 Bioinformatics

Bioinformatics pipeline frameworks have used templating languages to describe workflow processes with input and output parameters, for example, Common Workflow Language Specification (CWL)(cwl, 2016) uses YAML syntax and JSON format parameter files to define workflow logics with its required tools and parameters from command line interface (CLI). There are several implementations supporting the CWL such as Rabix(Kaushik et al., 2016), Arvados(arv, 2016), Galaxy, Taverna and Kronos(Taghiyar et al., 2016) to use templating languages in their workflow engines with ease accommodation of tool dependencies. In our case, we have a plan to use templating language to enable parallel processing on the cloud and HPC per independent component of workflows with expectation of better performance on computation and higher resource utilization on shared resource pool.

A few efforts have been made (Lee et al., 2012; Chae et al., 2013; Lee et al., 2016) to apply bioinformatics systems to cloud computing and HPC. Template deployment for bioinformatics frameworks would be developed with these work to extend existing tools with new technologies.

7 Case Studies: NIST Big Data Projects

NIST Big Data Public Working Group (NBD-PWG) (Technology. et al., 2015; Fox and Chang, 2014) reported 51 use cases across nine application domains including Government Operation, commercial, Defense, Healthcare and Life Sciences, Deep Learning and Social Media, The Echosystem for Research, Astronomy and Physics, Earth, Envionmental and Polar Science and Energy to understand Big Data requirements and advance the development of big data framework. We ought to keep up the same effort to support scientific community in regard to analyzing data with modern technologies and the part of this dissertation is gathering more use cases and requirements by reviewing publicly available big data applications.

7.1 Fingerprint Recognition

Fingerprint matching software (Flanagan, 2010; Flanagan, 2014) has been developed by National Institute of Standards and Technology (NIST) with special databases to identify patterns of fingerprint. NIST Biometric Image Software (NBIS) includes MINDTCT, a fingerprint minutiae detector and BOZORTH3, a minutiae based fingerprint matching program to process biometric analysis. MINDTCT program extracts the features of fingerprint such as ridge ending, bifurcation, and short ridge from the FBI's Wavelet Scalar Quantization (WSQ) images and BOZORTH3 runs fingerprint matching algorithm with the images generated by MINDTCT as part of fingerprint identification processing (Wegstein, 1982). In this use case, Apache Spark runs fingerprint matching on the Hadoop cluster with NIST Fingerprint Special Database 4 (Watson and Wilson, 1992) and stores results in HBase with the support of NoSQL database, Apache Drill. Addtional dataset from FVC2004 can be used as well with 1440 fingerprint impressions (Maio et al., 2004). Individual software represents a stack or a role in the context in which a set of tasks to complete a software deployment is included. Suggested software stacks (roles) for Fingerprint matching are:

- Apache Hadoop
- Apache Spark
- Apache HBase
- Apache Drill
- Scala

7.2 Human and Face Detection with OpenCV

Human and face detection have been studied during the last several years and models for them have improved along with Histograms of Oriented Gradients (HOG) for Human Detection (Dalal and Triggs, 2005a). OpenCV is a Computer Vision library including the SVM classifier and the HOG object detector for pedestrian detection and INRIA Person Dataset (Dalal and Triggs, 2005b) is one of popular samples for both training and testing purposes. In this use case, Apache Spark on Mesos clusters are deployed to train and apply detection models from OpenCV using Python API. Individual software represents a stack or a role in this context in which a set of tasks to complete a software deployment is included. Suggested software stacks (Roles) for human and face detection with OpenCV are:

- Apache Mesos
- Apache Spark
- OpenCV
- Zookeeper
- INRIA Person Dataset
- Python Analytics with HOG and Haar Cascades

7.3 Twitter Live Analysis

Social messages generated by Twitter have been used with various applications such as opinion mining, sentiment analysis (Pak and Paroubek, 2010), stock market prediction (Bollen, Mao, and Zeng, 2011), and public opinion polling (Cody et al., 2016) with the support of natual language toolkits e.g. nltk (Bird, 2006), coreNLP (Manning et al., 2014) and deep learning systems (Kim, 2014). Services for streaming data processing are important in this category. Apache Storm is widely used with the example of twitter sentiment analysis, and Twitter Heron, Google Millwheel, LindkedIn Samza, and Facebook Puma, Swift, and Stylus are available as well (Chen et al., 2016). Suggested software stacks (roles) for Twitter Live Analysis are:

- Apache Hadoop
- Twitter Heron
- Apache Storm
- Apache Flume
- Natural Language Toolkit (NLTK)

7.4 Big Data Analytics for Healthcare Data and Health Informatics

Several attempts have been made to apply Big Data framework and analytics in health care with various use cases. Medical image processing, signal analytics and genome wide analysis are addressed to provide efficient diagnostic tools and reduce healthcare costs (Belle et al., 2015) with big data software such as Hadoop, GPUs, and MongoDB. Open source big data ecosystem in healthcare is introduced (Raghupathi and Raghupathi, 2014) with examples and challenges to satisfy big data characteristics; volume, velocity, and variety (Zikopoulos, Eaton, and others, 2011). Cloud computing framework in healthcare for security is also discussed with concerns about privacy (Stantchev, Colomo-Palacios, and Niedermayer, 2014). Suggested software stacks (roles) for Big Data Analytics for Healthcare Data and Health Informatics are:

- Apache Hadoop
- Apache Spark
- Apache Mahout
- Apache Lucene/Solr
- MLlib

7.5 Spatial Big Data, Spatial Statistics and Geographic Information Systems

The broad use of geographic information system (GIS) has been increased over commercial and scientific communities with the support of computing resources and data storages. For example, Hadoop-GIS (Aji et al., 2013), a high performance spatial data warehousing system with Apache Hive and Hadoop, offers spatial query processing in parallel with MapReduce, and HadoopViz (Eldawy, Mokbel, and Jonathan, 2016), a MapReduce framework for visualizing big spatial data, supports various visualization types of data from satellite data to countries borders. Suggested software stacks (roles) for Spatial Big Data, Spatial Statistics and Geographic Information Systems are:

- Apache Hadoop
- Apache Spark
- GIS-tools
- Apache Mahout
- MLlib

7.6 Data Warehousing and Data Mining

Researches in data warehousing, data mining and OLAP have investigated current challenges and future directions over big data software and applications (Cuzzocrea, Bellatreche, and Song, 2013) due to the rapid increase of data size and complexity of data models. Apache Hive, a warehousing solution over a hadoop (Thusoo et al., 2009), has introduced to deal with large volume of data processing with the other research studies (Chen, 2010; He et al., 2011) and NoSQL platforms (Chevalier et al., 2015) have discussed with data warehouse ETL pipeline (Goodhope et al., 2012). Suggested software stacks (roles) for Data Warehousing and Data Mining are:

- Apache Hadoop
- Apache Spark
- MongoDB
- Hive
- Pig
- Apache Mahout
- Apache Lucene/Solr
- MLlib

7.6.1 Big Data Statistics from GitHub Repositories

Github.com has been used to provide version control and manage source code development along with diverse collaborators across countries. The popularity of github as a collaboration tool has been significantly increased and 4,995,050 repositories exist as of 12/27/2016 with 20-30 thousands daily added repositories. Therefore we report a repository statistics to understand software development related to big data applications and tools and to create a list of most common tools regarding to big data deployments. A development language distribution, most common libraries and packages, observations over a certain period and detection on recently added projects and tools are main part of the queries using github search API. We defined a set of keywords for projects to retrieve related github repositories, for example, fingerprint matching, fingerprint recognition, fingerprint verification, and biometric fingerprint are used to search github projects related to fingerprint recognition. Python and Java are most common languages among the six NIST projects (Table 6), although matlab is dominant in the fingerprint project. We also noticed that scientific python packages are commonly used to enable numerical computation, data analysis and visualization for these big data applications (Figure 10), whereas there are dependent packages for each project (Table 7). Tweepy, twitter API, is used in the twitter live analysis cases with NLTK, the natural language processing toolkit to complete sentiment analysis with tweets. Similarly, GIS projects use particular libraries for spatial analysis such as geopy and shapely. We observe that deep learning python packages e.g. caffe have recently added to github repositories. Statistics (tables 8 to 13) show that popular github repository examples related to the six nist projects started in 2016. Each github project has different language preferences with various libraries and packages therefore recent activities can be observed, for example, deep learning software such as Keras, Theano, mxnet and Caffe is adopted among multiple projects.

7.7 Datasets

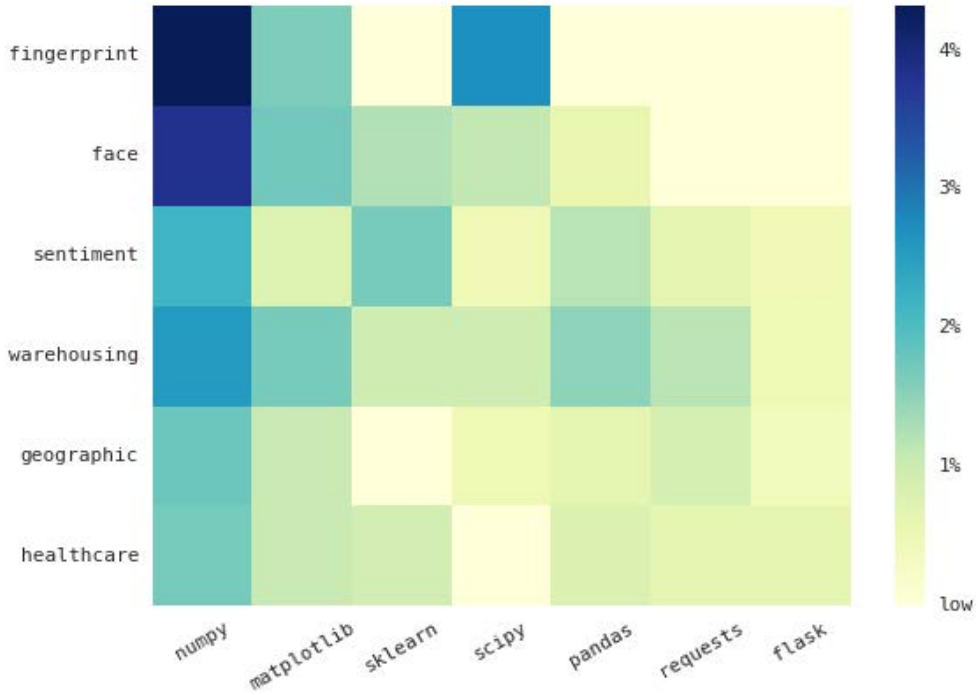
Finding relevant datasets for particular applications is another challenge for the big data ecosystem because of its difficulty of collecting data from different sources (Kim, Trimi, and Chung, 2014), complexity and diversity (Hashem et al., 2015). Community contributed lists of public datasets (Cohen and Lo, 2014) provide structured information with a specific location to access data and a category to describe itself. We intend to generate linked json data for datasets and applications in big data ecosystem based on these lists because it connects scattered data and software in an organized way. Table 14 shows the data source from different sectors, academia(.edu or .ac.), government(.gov), organization(.org), industry(.com or .net), and international(country suffix), among the seven categories of the lists. Entire categories are available online: `https://github.com/lee212/bd_datasets`. Listing 15 also shows a example of the linked data between MNIST dataset and two software available on github.com.

Topic	C++	Python	Java	Matlab	JS	C#	C	R	Ruby	Scala	Count*
Fingerprint (7.1)	15%	11%	13%	20%	3%	16%	8%	0%	1%	5%	43
Face (7.2)	26%	21%	12%	9%	7%	5%	2%	2%	1%	.02%	538
Twitter (7.3)	2%	35%	15%	.6%	9%	2%	1%	10%	3%	1%	1429
Warehousing (7.6)	3%	27%	18%	2%	10%	3%	1%	10%	4%	1%	3435
Geographic (7.5)	5%	15%	27%	4%	15%	3%	5%	7%	3%	16%	6487
Healthcare (7.4)	2%	13%	19%	2%	14%	5%	1%	10%	6%	2%	132

Table 6: Language Distribution of Topics related to those in the NIST collection on Github

* Count: average number of github.com repositories.

Figure 10: Scientific Python Packages used in NIST Projects (collected from Github)



Python Package	Description	Fingerprint	Face	Twitter	Warehousing	Geographic	Healthcare
cv2	OpenCV	✓	✓				
skimage	Image Processing		✓				
PIL	Python Imaging Library		✓				
caffe	Deep Learning		✓				
nltk	Natural Language Toolkit			✓			
tweepy	Twitter for Python			✓			
BeautifulSoup	Screen-scraping library			✓	✓		
gensim	Topic Modelling			✓	✓		
geopy	Geocoding library					✓	
shapely	Geometric Analysis					✓	
django	Web framework				✓		✓

Table 7: Additional Python packages found in NIST Collection

Title	Description	Language	Start Date	Popularity	Dependency
OpenFace	an open source facial behavior analysis toolkit	c++	March, 2016	725 (305)	OpenCV, dlib, boost, TBB
Picasso face detection transformation	An Android image transformation library providing cropping above Face Detection (Face Centering) for Picasso	Java	July, 2016	528(56)	Square Picasso
MTCNN face detection alignment	Joint Face Detection and Alignment using Multi-task Cascaded Convolutional Neural Networks	Matlab	September, 2016	226(162)	Caffe, Pdollar toolbox
facematch	Facebook Face Recognition wrapper	JavaScript	January, 2016	132 (41)	fbgraph, request, body-parser, express
mxnet mtcnn face detection	MTCNN face detection	Python	October, 2016	99 (47)	OpenCV, mxnet

Table 8: Example Projects Recently Created Regarding to Face Detection

Title	Description	Language	Start Date	Popularity	Dependency
CNN fingerprint	fingerprint verification using convolution neural networks	Python	December, 2016	0 (1)	Keras, Theano
fingerprint recognizer	Web app for human fingerprint recognition with math on Node.JS 7	JavaScript	December, 2016	0 (1)	jimp
neurodactyl	C++ software tool for fingerprint recognition based on neural networks	C++	November, 2016	0 (0)	OpenCV, Bozorth3, FANN

Table 9: Example Projects Recently Created Regarding to Fingerprint Matching

Title	Description	Language	Start Date	Popularity	Dependency
tidytext	Text mining using dplyr, ggplot2, and other tidy tools	R	March, 2016,	310 (42)	dplyr, ggplot2, tidyr, broom
Bayesian sentiment analysis	Pragmatic & Practical Bayesian Sentiment Classifier	Kotlin	August, 2016	213 (19)	Apache Lucene
Hotel review analysis	Sentiment analysis and aspect classification for hotel reviews using machine learning models with MonkeyLearn	Python	April, 2016	154 (34)	Scrapy, ElasticSearch, Kibana, nltk, pandas
Sentiments	Sentiments is an iOS app written in Swift that analyzes text for positive or negative sentiment	Swift	February, 2016	146 (8)	Alamofire, SwiftyJSON, HPE Haven OnDemand
Sentiment Analysis Twitter	We use different feature sets and machine learning classifiers to determine the best combination for sentiment analysis of twitter	Python	October, 2016	139 (42)	twitter, mdp

Table 10: Example Projects Recently Created Regarding to Twitter Analysis

Title	Description	Language	Start Date	Popularity	Dependency
gpq	A collection of tools for mining government data	Jupyter Notebook	June, 2016	128 (10)	Google BigQuery
reair	a collection of easy-to-use tools for replicating tables and partitions between Hive data warehouses	Java	March, 2016	91 (42)	Hadoop, Hive
SpawnTracker	Probably the most efficient large area long duration tracker for pokemon go data mining	Protocol Buffer, Python	July, 2016	34 (9)	s2sphere, GeoJSON, protobuf, pgoapi
idbr	An R interface to the US Census Bureau International Data Base API	R	January, 2016	23 (12)	dplyr, ggplot2, ggthemes
get-tiger	Make workflow for downloading Census geodata and joining it to survey data	Makefile	February, 2016	20 (0)	GDAL

Table 11: Example Projects Recently Created Regarding to Data Warehousing

Title	Description	Language	Start Date	Popularity	Dependency
Pokemon Go Move	Pokemon GO GPS Emulator with Built-In Pokemon/Pokestop/Gym Map	Python	July, 2016	401 (74)	geopy, s2sphere
d3-geo	Geographic projections, spherical shapes and spherical trigonometry	Javascript	March, 2016	112 (35)	d3-array
Geospatial messenger	Geospatial messenger application written with Spring Boot + Kotlin + PostgreSQL	Kotlin	March, 2016	105 (22)	Spring Boot, PostgreSQL
DotSpatial	Geographic information system library written for .NET	C#	April, 2016	94 (52)	
geo.lua	A helper library for Redis geospatial indices	Lua	February, 2016	74 (7)	

Table 12: Example Projects Recently Created Regarding to Geographic Information Systems

Title	Description	Language	Start Date	Popularity	Dependency
Temperate	a healthcare application that aims to make healthcare more accessible to everyone, everywhere	JavaScript, PHP	January, 2016	91 (7)	MySQL
Computational Healthcare	Analyze large healthcare datasets & build machine learning models using TensorFlow	Python	December, 2016	41 (15)	
healthcareai	R tools for healthcare machine learning	R	June, 2016	24 (10)	SQL Server
datasus	An Interface for the Brazilian Public Healthcare Data Repository (DATASUS) for the R Language	R	June, 2016	11 (6)	
RETAIN	Interpretable Predictive Model in Healthcare using Reverse Time Attention Mechanism	Python	August, 2016	6 (2)	Theano, CUDA

Table 13: Example Projects Recently Created Regarding to Healthcare Data

Category	Academia	Government	Organization	Industry	International	Total
GIS	1	3	5	9	5	23
Healthcare	0	6	3	1	1	11
Image Processing	11	0	4	2	5	18
Natural Language	7	0	8	7	6	26
Social Networks	8	0	7	5	5	24
Climate/Weather	2	6	3	2	4	16
Energy	2	2	5	1	5	15

Table 14: Public Dataset sectors of acamedia, government, organization, industry and international

Task	Completion
Application & Infrastructure Deployment	
Case Study: NIST Project	December 2016
Proposal	March, 2017
Integrating Ansible with Container Images	
- ICA3PP 2017	March 2017
Pairing Ansible Roles and Infrastructure Provisioning	
- HPCS 2017	March 2017
Automated Deployments with NIST Big Data	
- ICCAC 2017	May 2017
Scientific Applications	
Bioinformatics Integration	June 2017
- BIBM 2017	
Case Study: Containerized tool deployment of Galaxy Workflow	July 2017
Dissertation	
Writing	August 2017
Defense	October 2017

Table 15: Timeline for completion of this thesis

8 Research Plan

Table 15 provides a summary of the remaining tasks and their expected completion date. Some comments and risk assessments follow.

ICA3PP, HPCS, ICCAC The target proceedings are addressed

9 Dissertation Chapters

1. Introduction
2. Background
3. Template-based Infrastructure Provisioning
4. DevOps Software Deployment
5. Event-driven Computing with CRIU
6. NIST Use Cases
7. Curated Package Recommender for Dynamic Computing Environment
8. Integration with Bioinformatics
9. Software Defined Systems with Serverless Paradigm
10. Conclusions

10 Summary

Software defined systems presents manageable, dynamic and flexible computing resources with the serverless paradigm to ensure simplicity of data processing but guaranteed performance of computation through infrastructure provisioning. The combination of DevOps tools and Templates removes a barrier of using systems from complicated software stacks and the shareability and elasticity are inherited to the software defined systems on both HPC and Clouds.

11 Related Work

11.1 Template deployment

Several infrastructure provisioning tools have emerged to offer transparent and simple management of cloud computing resources over the last few years. Templates which are structured documents in a YAML or JSON format define infrastructure with required resources to build and ensure identical systems to create over time. A collection of Amazon cloud services are provisioned through Cloudformation (clo, 2010) templates which is an Amazon infrastructure deployment service. OpenStack Heat (osh, 2012) was started with similar template models to Amazon but has extended with other OpenStack services e.g. Telemetry, monitoring and autoscaling service to build multiple resources aa a single unit. The Topology and Orchestration Specification for Cloud Applications (TOSCA) (Wettinger, Breitenbücher, and Leymann, 2014; Binz et al., 2014) proposes standardization over different cloud platforms with XML-based language and several studies have been made with TOSCA (Kopp et al., 2013; Breiter et al., 2014; Qasha, Cala, and Watson, 2015). These tools have been addressed with issues in a few studies (Yamato et al., 2014; Fox et al., 2015) and one of identified issues is that individual specification of supported resources, functions, type names, and parameters prevents building and sharing infrastructure blueprints across cloud platforms.

11.2 DevOps Tools

In the DevOps phase, configuration management tools automates software deployment to provide fast delivery process between development and operations (Ebert et al., 2016). Instructions to manage systems and deploy software are written in scripts although different formats i.e. YAML, JSON, and Ruby DSL and various terminologies i.e. recipes, manifests, and playbooks are used. There are notable tools available to achieve automated software deployment. Puppet and Chef are identified configuration management tools written in Ruby and these tools manage software on target machines regarding to installation, execution in a different state e.g. running, stopping or restarting, and configuration through the client/server mode (also called master/agent). Ansible is also recognized as a configuration management tool but more focusing on software deployment using SSH and no necessity of agents on target machines. With the experience from class projects and NIST use cases, a few challenging tasks are identified in DevOps tools, a) offering standard specification of scripts to ease script development with different tools, and b) integrating container technologies towards microservices.

11.3 Container technology

While existing container software, e.g. docker, rkt, lxd, offers various features with outstanding performance there are number of new tools recently developed with the support on HPC. Shifter from NERSC on Cray XC30 with GPU (Benedicic et al., 2016) has introduced and singularity from LBNL (Kurtzer, 2016) as well. These new implementations are typically for heavy workloads which requires checkpoint/restart for long running applications and easy deployment of required software stacks in a user space.

11.4 TOSCA Ecosystem - (Topology and Orchestration Specification for Cloud Applications)

TOSCA is a standardized management of cloud services with applications using workflow technologies and the specification (OASIS, 2013) to ensure reproducibility.

One of goals that TOSCA aims is to provide portability of cloud service management along with their environments (Binz et al., 2012), There are a few terminologies in this context. A service template contains all information about operation and management including a topology of cloud services at a top level of abstraction. Plans, Nodes and Relations are included in the service template. A service topology is a description of service components (nodes) and its relations to others therefore the structure of systems to build is represented. Plans have instructions about operations and managements through workflow technology. Orchestration of service operation and management is described in plans with WSDL, REST or scripts. In addition verification (inspection) of the topology and retrieval or modification of service instance information are supported by plans. With BPMN and BPEL workflow languages, TOSCA plans are portable in differement management envrionments to adopt.

OpenTOSCA is a runtime supporting imperative processing of TOSCA-based cloud applications (Binz et al., 2013). The core components of OpenTOSCA are implementation artifact engine, plan engine, container API and plan portability API where build plan conducts management operations and deployment of applications with OASIS TOSCA packaging format CSAR.

Eclipse Winery is a graph based modeling tool for TOSCA-based cloud applications using HTML and Eclipse environment (Kopp et al., 2013). The frontend components with GUI of Winery are divided by the DevOps paradigm to ease collaboration between developers and operators. Topology Modeler provides visual topology modeling to operators with seven elements; relationship template, relationship constraint, node template, deployment artifact, requirement, capability and policy. Element Manager provides controls of technical details to system experts such as types, implementations, policy templates and configurations. BPMN4TOSCA Modeler is added later to support in creating BPMN elements and structures used in TOSCA plans through web-based graphical user interface. Winery uses databases (called repository) to store TOSCAL models in CSAR format which is a TOSCA Cloud Service ARchive application package.

Visual notation for TOSCA (named Vino4TOSCA) (Breitenbücher et al., 2012) has introduced with explicit design principles and requirements. Nine requirements for desigining effective visual notations are defined as: R1 Semiotic Clarity, R2 Perceptual Discriminability, R3 Semantic Transparency, R4 Complexity Management, R5 Cognitive Integration, R6 Visual Expressiveness, R7 Dual Coding, R8 Graphic Economy, and R9 Cognitive Fit. The requirements for constructing TOSCA-specific notations are: R10 Completeness, R11 Semantic Correctness, R12 Extensibility, and R13 Compact Representation. The requirements for usability and use experience are: R14 Suitability for the Task, R15 Self-descriptiveness, R16 Simplicity, and R17 User Satisfaction.

Automated provisioning of cloud infrastructure is described with the TOSCA topology template and the plan where the structure of cloud applications is defined in the template and an executable provisioning workflow (called plan) is generated based on the template (Breitenbücher et al., 2014a). In practical terms, Winery, topology modeling GUI tool, creates a service template with nodes and relationships to depict a system structure in CSAR format and OpenTOSCA, a TOSCA runtime environment, executes the plans after the process of generating provisioning order graph, provisioning plan skeleton and executable provisioning plan in workflow languages i.e. BPEL and BPMN.

There are additional tools supporting the TOSCA ecosystem. Vinothek (Breitenbücher et al., 2014b) is a web interface of application manager on the TOSCA runtimes using Java Server Pages and HTML5. It accepts user inputs for launching applications on the web such as input parameters and runtime-specific information. TOSCAMART (TOSCA-based Method for Adapting and Reusing application Topologies) (Soldani et al., 2016) offers a method to build desired environments on any cloud provider by assembling fragments of existing TOSCA topologies. This approach includes finding reusable fragments of the topology from repositories, choosing candidates by rates and filters and adapting final candidate fragments through ratings as a process of building desired environments.

Title	Description	Function	Language	Repository	Extensibility
OpenTOSCA	TOSCA Runtime Environment	Runtime system	Java	github.com /OpenTOSCA/container	BPMN, BPEL
Winery	Web-based environment for modeling TOSCA topologies	Front-end GUI	Java	github.com /eclipse/winery	BPMN
BPMN4TOSCA	Extension for TOSCA management plans	Extensions	Javascript	github.com /winery/BPMN4TOSCAModeler	BPMN
Vinothek	Cloud application management	Front-end GUI	Java	github.com /OpenTOSCA/vinothek	CSAR
TOSCA-MART	Methods for adapting and reusing TOSCA cloud applications	Extensions	Java	github.com /jacopogiallo/TOSCA-MART	CSAR

Table 16: Components of TOSCA Ecosystem

- BPMN - Business Process Model and Notation
- BPEL - Business Process Execution Language
- CSAR - TOSCA Cloud Service ARchive

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