

Scaling up Interactive Data Analysis in Jupyter Lab: From Laptop to HPC

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COMPUTING WITHOUT BOUNDARIES

EXPANS-

SAN DIEGO SUPERCOMPUTER CENTER

UNIVERSITY OF CALIFORNIA SAN DIEGO

Outline

- When to run on Expanse
- Setup a portable and reproducible software environment
- Run Jupyter Lab on Expanse
- Scale up calculations on CPU/GPU - Dataframes
- Measure parallel efficiency
- Get ready to use Expanse: accounts, allocations

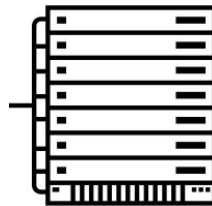
When to run on Expanse

Laptop/Desktop

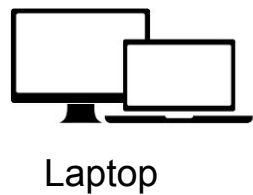


- Coding
- Exploratory phase
- Small datasets
- Run on single or few cores

Expanse

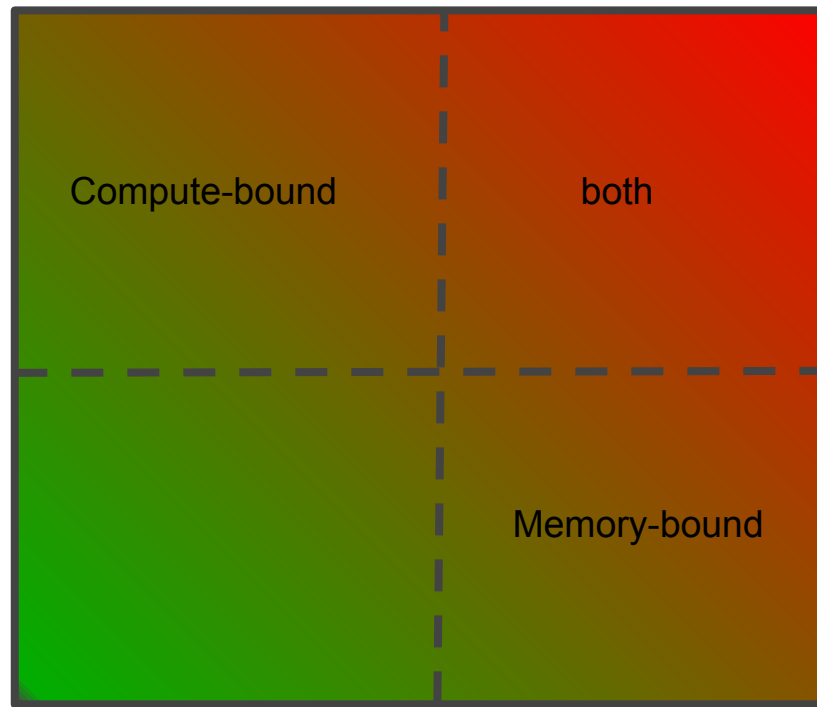


- Scaling up to
 - large datasets
 - many datasets
 - long runtimes
- Run on many cores
- Run on GPU



Laptop

Compute



Compute-bound

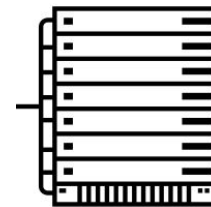
both

Memory-bound



fit into memory

Memory



HPC

Setup a portable and reproducible software environment

From laptop to HPC

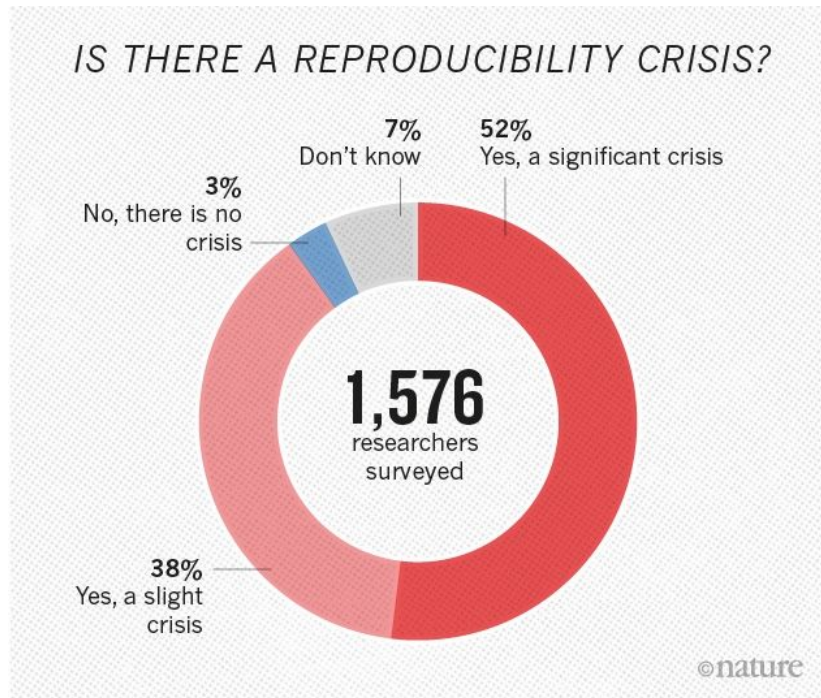
Reproducibility Crisis?

“More than 70% of researchers have tried and failed to reproduce another scientist's experiments, and more than half have failed to reproduce their own experiments.”

Nature, 2016, M. Baker, 1,500 scientists lift the lid on reproducibility

“Nature journal editors ... will, on a case-by-case basis, ask reviewers to check how well the code works.”

Nature, 2018, Does your code stand up to scrutiny?



Reproducibility*

obtaining **consistent** results using

same input data or parameters

same computational steps, methods, and code

same analysis conditions

Reusability

obtaining **new** results using

different input data or parameters

same computational steps, methods, and code

same analysis conditions

Scalability

obtaining **new** results using

large input data or parameter sets

same computational steps, methods, and code

same analysis conditions

* L. Barba, https://figshare.com/articles/Next_in_Reproducibility_standards_policies_infrastructure_and_human_factors/8194328/1

Tools and Infrastructure



Computational notebooks:
combine documentation,
code, and results



git

Version-control system
for tracking changes in
source code



GitHub

Source code
repository



Open-source package
and environment
management system



Container that packages
software and OS in a
portable way




Scalable compute infrastructure

 OPEN ACCESS

EDITORIAL

Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks

Adam Rule, Amanda Birmingham, Cristal Zuniga, Ilkay Altintas, Shih-Cheng Huang, Rob Knight, Niema Moshiri, Mai H. Nguyen, Sara Brin Rosenthal, Fernando Pérez, Peter W. Rose 

Published: July 25, 2019 • <https://doi.org/10.1371/journal.pcbi.1007007>

295
Save

54
Citation

48,876
View

1,039
Share

Paper: <https://doi.org/10.1371/journal.pcbi.1007007>

Git repo: <https://github.com/jupyter-guide/ten-rules-jupyter>

Reproducible Environments



- Beginner
- Experience with Conda
- Exploratory development
- Frequently changing dependencies
- Easy to compose an environment with many dependencies
- Run on single node on Expanse
- Supported on Linux, Mac, Windows
- Run on native OS



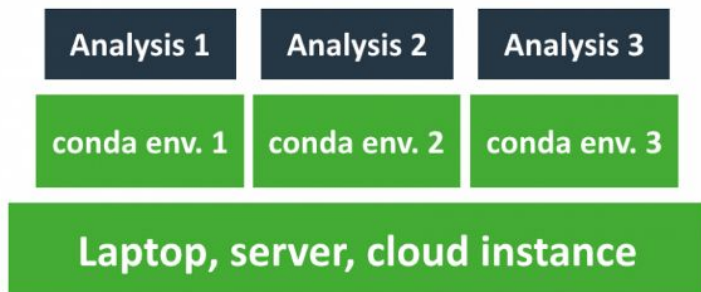
- Advanced user
- Experience with containers
- Production environment
- Often setup for a single tool
- Optimized containers for Expanse
 - pytorch, tensorflow, ...
 - support for multi-node
- Supported on Linux
- Mac, Windows requires a VM
- Run on packaged OS, e.g. Ubuntu



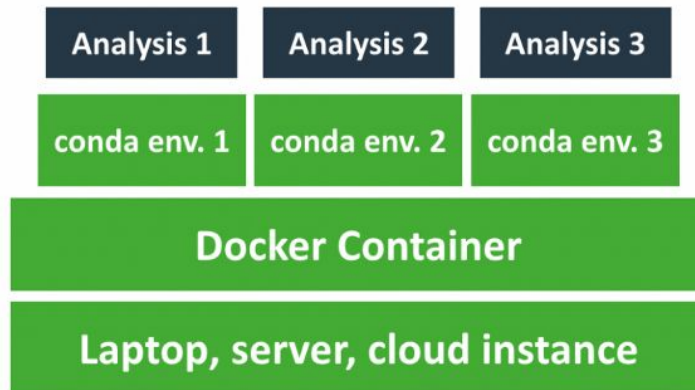
Data Scientist



DevOps

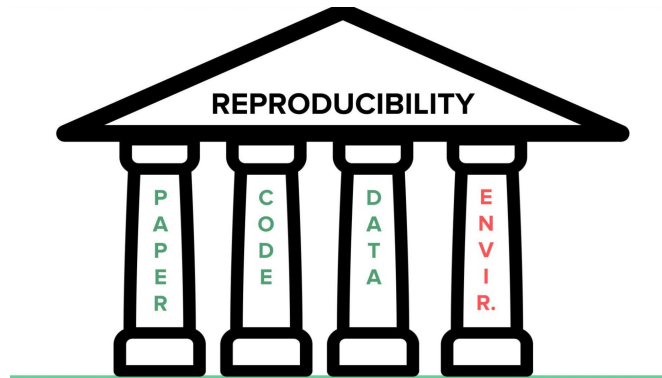


Data Science Development



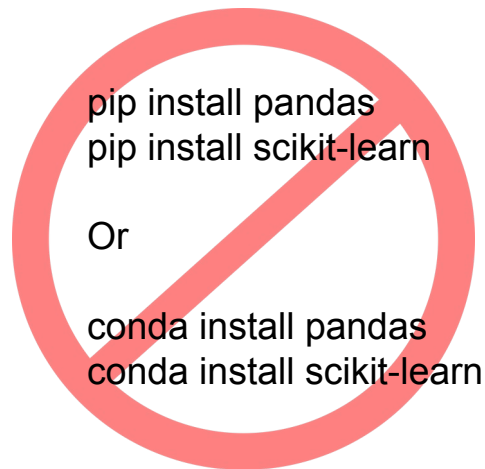
Data Science Deployment

Source: <https://medium.com/@patrickmichelberger/getting-started-with-anaconda-docker-b50a2c482139>



- **Package management system**
 - Conda installs, runs, and updates open source packages (e.g., NumPy, Pandas) and their dependencies, while checking compatibility with all preexisting packages.
- **Environment management system**
 - Conda allow you to create, save, load and switch between multiple environments on your local computer, as well as share instructions for how to recreate that environment on a different computer.
- **Multi-platform (Windows, MacOS, and Linux)**
- **Multi-language (Python, R, Ruby, Scala, Java, JavaScript, C/ C++, etc.)**

Why Conda Environments?



Directly installing packages into your base environment will lead to version conflicts, errors, and non-reproducible results.

environment_1

python=3.7
pandas=0.25.0
scikit-learn=0.20.0

environment_2

python=3.9
pandas=1.2.4
scikit-learn=0.24.2

By creating conda environments, multiple versions of software packages can co-exists without interference.

Conda environment are portable and can be installed on multiple platforms.

Define a Conda Environments

Create an **environment.yml** file in the top level of a Git Repository (<https://github.com/sbl-sdsc/df-parallel>)

```
name: df-parallel
```

```
channels:
```

- conda-forge
- anaconda

```
dependencies:
```

- python=3.9
- jupyterlab=3
- ipywidgets=7.7.1
- matplotlib=3.5.2
- seaborn=0.11.2
- papermill=2.3.4
- dask=2022.05.2
- pyspark=3.3.0
- pyarrow=7.0.0
- openjdk=11.0.15

```
variables:
```

```
# SPARK conf directory contains logging configuration
SPARK_CONF_DIR: ../conf
SPARK_DRIVER_MEMORY: 16G
SPARK_DRIVER_MAXRESULTSIZE: 4G
SPARK_WORKER_MEMORY: 4G
```

Use the same name as your Git repository

Specify the channels where to look for packages. Order matters!
The conda-forge channel has newer versions than anaconda.

Specify (“**pin**”) version number to ensure reproducibility and compatibility.

Specify non-Python packages (e.g., Java).

Set environment variables (e.g., configuration options).

Create a Conda Environment

Prerequisite: Miniconda3 (light-weight, preferred) or Anaconda3 installed

<https://docs.conda.io/en/latest/miniconda.html>

Create a Conda environment

```
conda env create -f environment.yml  
or  
mamba env create -f environment.yml (faster)
```



Mac, Windows, Linux

Activate a Conda environment

```
conda activate <environment_name>
```

Run Jupyter Lab

```
jupyter lab
```

Deactivate conda environment

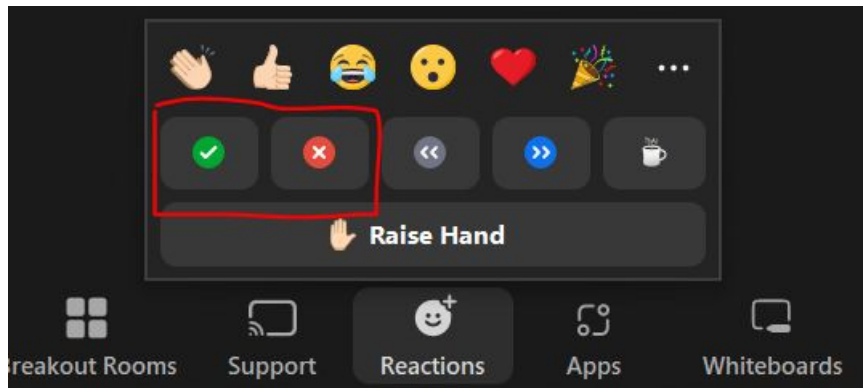
```
conda deactivate
```





Expense: **Do not** create a Conda environment in your home directory (network file system)
-> Use the **galileo** script!

Run Jupyter Lab on Expanse

Feedback using Zoom Reactions



We will use Reactions to get feedback during the hands-on exercises

- Yes  I've successfully completed the task
- No  I have a problem
(go to Slack and describe your problem or raise your hand)

Expanse Portal

Expanse Portal Apps Files Jobs Clusters Interactive Apps



SDSC

The Expanse portal provides an integrated, and easy to use interface to access Expanse HPC resource.

With the portal, researchers can manage files (create, edit, move, upload, and download), view job templates for various applications, submit and monitor jobs, run interactive applications, and connect via SSH. The portal has no end-user installation requirements other than access to a modern up-to-date web browser

Pinned Apps A featured subset of [all available apps](#)



Active Jobs

System Installed App



Home Directory

System Installed App



Job Composer

System Installed App



expanse Shell Access

System Installed App



MATLAB

System Installed App



RSTUDIO

System Installed App



Allocation and Usage
Information

System Installed App



Jupyter

System Installed App

- Login with your XSEDE credentials (trainxx):
<https://portal.expanse.sdsc.edu/>
- Open a terminal window

Jupyter Notebook (CPU) →

Jupyter Notebook (GPU) →

Testing (CPU) →

Testing (GPU) →

Partition Name	Max Walltime	Max Nodes/Job	Max Running Jobs	Max Running + Queued Jobs	Charge Factor	Notes
compute	48 hrs	32	32	64	1	Exclusive access to regular compute nodes; <i>limit applies per group</i>
ind-compute	48 hrs	32	32	64	1	Exclusive access to Industry compute nodes; <i>limit applies per group</i>
shared	48 hrs	1	4096	4096	1	Single-node jobs using fewer than 128 cores
ind-shared	48 hrs	1	32	64	1	Single-node Industry jobs using fewer than 128 cores
gpu	48 hrs	4	4	8 (32 Tres GPU)	1	Used for exclusive access to the GPU nodes
ind-gpu	48 hrs	4	4	8 (32 Tres GPU)	1	Exclusive access to the Industry GPU nodes
gpu-shared	48 hrs	1	24	24 (24 Tres GPU)	1	Single-node job using fewer than 4 GPUs
ind-gpu-shared	48 hrs	1	24	24 (24 Tres GPU)	1	Single-node job using fewer than 4 Industry GPUs
large-shared	48 hrs	1	1	4	1	Single-node jobs using large memory up to 2 TB (minimum memory required 256G)
debug	30 min	2	1	2	1	Priority access to shared nodes set aside for testing of jobs with short walltime and limited resources
gpu-debug	30 min	2	1	2	1	Priority access to gpu-shared nodes set aside for testing of jobs with short walltime and limited resources; <i>max two gpus per job</i>
preempt	7 days	32		128	.8	Non-refundable discounted jobs to run on free nodes that can be pre-empted by jobs submitted to any other queue
gpu-preempt	7 days	1		24 (24 Tres GPU)	.8	Non-refundable discounted jobs to run on unallocated nodes that can be pre-empted by higher priority queues

Example using Galyleo

Prepend path to galyleo to your path (e.g., append to ~/.bash_profile file)

```
export PATH="/cm/shared/apps/sdsc/galyleo:${PATH}"
```

1. Clone the Git repository

```
https://github.com/sbl-sdsc/df-parallel.git
```

2. Launch your Jupyter Notebook session using a Conda environment.yml file

```
galyleo launch --account <account_number> --partition shared --cpus 10  
--memory 20 --time-limit 00:30:00 --conda-env df-parallel --conda-yml  
"${HOME}/df-parallel/environment.yml" --mamba
```

3. Copy and paste generated URL into your web browser

```
https://anchovy-passion-placidly.expense-user-content.sdsc.edu?token=48ee984b9ea07a96c17aaec000bc5fcf
```

How to Create and Use a Packed Conda Environment

Galileo creates a Conda environment on the fly. If you use an environment often, you can save a packed Conda environment.



Create packed Conda Environment (**df-parallel.tar.gz**)

```
./df-parallel/pack.sh --account <account_number> --conda-env df-parallel  
--conda-ym1 "${HOME}/df-parallel/environment.yml"
```

Use packed Conda Environment

```
galileo launch --account <account_number> --partition shared --cpus 8 --memory 16  
--time-limit 00:30:00 --conda-env df-parallel  
--conda-pack "${HOME}/df-parallel.tar.gz"
```

More details about Conda environment: <https://github.com/mkandes/galileo#conda-environments>

Progress Bar and Jupyter Launch

Satellite Reverse Proxy Service

SDSC Expanse

Job State: Proxied



In Queue
Job has not yet started.

Running
Job has started, but has not redeemed Satellite Token.

Mapped
Job has redeemed Satellite Token, but no proxy entry exists yet.

Proxied
Proxy entry created, ready to go!

Dead
Job died or exited, no further progress will occur.

anchovy-passion-placidly.expanse-user-content.sdsc.edu/lab/tree/df-parallel/...

File Edit View Run Kernel Tabs Settings Help

Filter files by name

Name	Last Modified
1-DownloadData.ipynb	17 hours ago
2-PandasDataframe.ipynb	17 hours ago
3-DaskDataframe.ipynb	4 days ago
4-SparkDataframe.ipynb	4 days ago
5-CudaDataframe.ipynb	17 hours ago
6-DaskCudaDataframe.ipynb	4 days ago

1-DownloadData.ipynb

Download Gene Inform

This notebook downloads a list of genes for [NCBI](#).

To ensure platform independence, this notet Python libraries to download and unzip a cor

```
[1]: import os
```

Open from Path...
Open from URL...

New View for Notebook
New Console for Notebook

Close Tab
Close and Shutdown Notebook
Close All Tabs

Save Notebook
Save Notebook As...
Save All

Reload Notebook from Disk
Revert Notebook to Checkpoint
Rename Notebook...

Download

Save and Export Notebook As...

Save Current Workspace As...
Save Current Workspace

Print...
Log Out

Shut Down

File-> Shut Down to terminate process,
or job continues to use up your allocation!

Running the Dataframe Examples

Clone the Git repo

```
git clone https://github.com/sbl-sdsc/df-parallel.git
```

Run on CPU (Pandas, Dask, Spark dataframes)

```
galyleo launch --account <account_number> --partition shared --cpus 10  
--memory 20 --time-limit 01:00:00 --conda-env df-parallel  
--conda-yml "${HOME}/df-parallel/environment.yml" --mamba
```

Run on GPU (Pandas, Dask, Spark, cuDF, Dask-cuDF dataframes)

```
galyleo launch --account <account_number> --partition gpu-shared --cpus 10  
--memory 92 --gpus 1 --time-limit 01:00:00 --conda-env df-parallel-gpu  
--conda-yml "${HOME}/df-parallel/environment-gpu.yml" --mamba
```

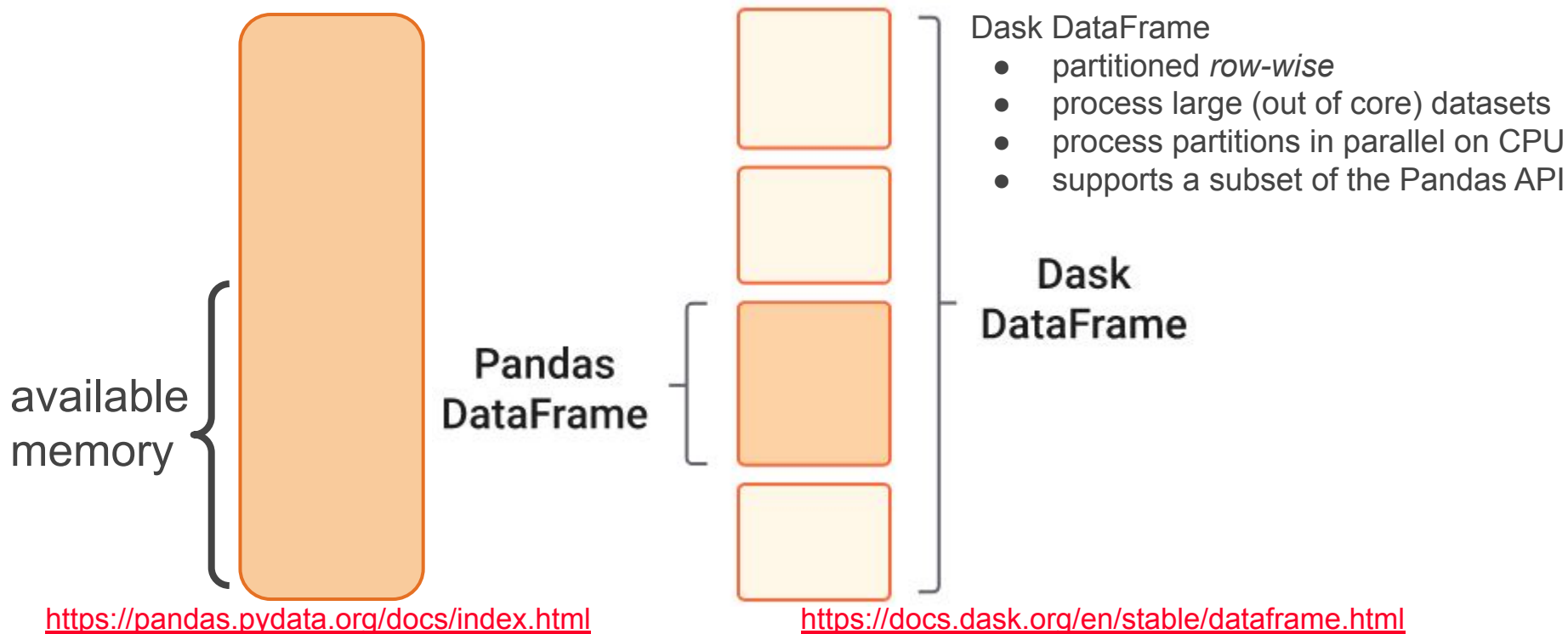
Task 1

- Launch Jupyter Lab using Galyleo script
- Follow the instructions in section 6.2: Task 1
https://github.com/sdsc/sdsc-summer-institute-2022/tree/main/6.2_scaling_up_interactive_data_analysis_jupyter_lab#task-1-launch-jupyter-lab-on-expanse-using-a-conda-environment

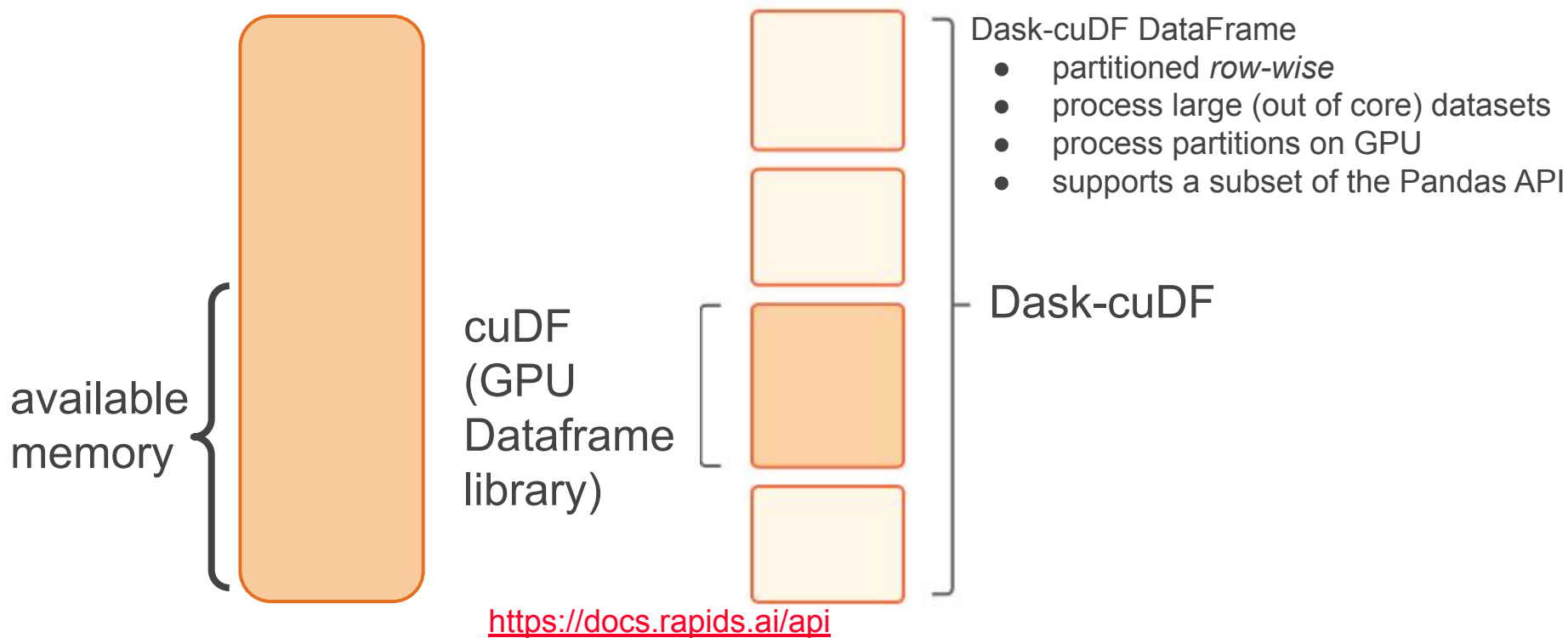
Scale up calculations on CPU/GPU

Example: Data Analysis with Dataframes

Processing large Datasets on CPU



Processing large Datasets on GPU



Columnar Storage Format - Parquet

Query and space efficient file format (default: Snappy compression)

Vertical partitioning (projection push down) + Horizontal partitioning (predicate push down) = Read only the data you need!

a	b	c
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5

+

a	b	c
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5

=

a	b	c
a1	b1	c1
a2	b2	c2
a3	b3	c3
a4	b4	c4
a5	b5	c5



@EmrgencyKittens

Horizontal partitioning uses column min/max statistics from Parquet metadata.

<https://www.slideshare.net/julienledem/if-you-have-your-own-columnar-format-stop-now-and-use-parquet>

Vertical & Horizontal Partitioning

```
column_names = ["GeneID", "Symbol", "Synonyms", "description", "type_of_gene", "#tax_id", "chromosome"]  
filters=[["type_of_gene", "==", "protein-coding"]]
```

```
# Parquet
```

```
genes = pd.read_parquet(filename, columns=column_names, filters=filters)
```

```
# Dask
```

```
genes = dd.read_parquet(filename, columns=column_names, filters=filters)
```

```
# cuDF
```

```
genes = cudf.read_parquet(filename, columns=column_names, filters=filters)
```

```
# Dask-cuDF (filter does not work or is not fully implemented)
```

```
genes = dask_cudf.read_parquet(filename, columns=column_names)
```

```
genes = genes[genes["type_of_gene"] == "protein-coding"]
```

```
# Spark
```

```
genes = spark.read.parquet(filename)
```

```
genes = genes.select(column_names)
```

```
genes = genes.filter("type_of_gene == 'protein-coding'")
```


Creating Parquet “Files” with Dask

```
genes = dd.read_csv(input, dtype=str, sep="\t")
```

```
genes.to_parquet(output, write_index=False,  
write_metadata_file=True, engine="pyarrow")
```

```
genes = dd.read_csv(input, dtype=str, sep="\t")
```

```
genes.to_parquet(output, write_index=False,  
write_metadata_file=True, engine="pyarrow",  
partition_on=["type_of_gene"])
```

```
[xdtr104@login02 ~]$ ls -lh gene_info.parquet/  
total 1.2G  
-rw-r--r-- 1 xdtr104 uic157 6.9K Aug  4 10:14 _common_metadata  
-rw-r--r-- 1 xdtr104 uic157 161K Aug  4 10:14 _metadata  
-rw-r--r-- 1 xdtr104 uic157 9.9M Aug  4 10:14 part.0.parquet  
-rw-r--r-- 1 xdtr104 uic157 9.8M Aug  4 10:14 part.1.parquet  
-rw-r--r-- 1 xdtr104 uic157 16M Aug  4 10:14 part.10.parquet  
-rw-r--r-- 1 xdtr104 uic157 18M Aug  4 10:14 part.11.parquet  
-rw-r--r-- 1 xdtr104 uic157 20M Aug  4 10:14 part.12.parquet  
-rw-r--r-- 1 xdtr104 uic157 17M Aug  4 10:14 part.13.parquet  
-rw-r--r-- 1 xdtr104 uic157 19M Aug  4 10:14 part.14.parquet  
-rw-r--r-- 1 xdtr104 uic157 18M Aug  4 10:14 part.15.parquet  
-rw-r--r-- 1 xdtr104 uic157 20M Aug  4 10:14 part.16.parquet  
-rw-r--r-- 1 xdtr104 uic157 21M Aug  4 10:14 part.17.parquet  
-rw-r--r-- 1 xdtr104 uic157 19M Aug  4 10:14 part.18.parquet  
-rw-r--r-- 1 xdtr104 uic157 20M Aug  4 10:14 part.19.parquet
```

- Parquet files are typically directories of files.

```
[xdtr104@login02 ~]$ ls -lh gene_info.parquet/  
total 698K  
-rw-r--r-- 1 xdtr104 uic157 6.9K Aug  4 16:16 _common_metadata  
-rw-r--r-- 1 xdtr104 uic157 1.5M Aug  4 16:16 _metadata  
drwxr-xr-x 2 xdtr104 uic157  4 Aug  4 16:16 'type_of_gene=biological-region'  
drwxr-xr-x 2 xdtr104 uic157  68 Aug  4 16:15 'type_of_gene=miscRNA'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=ncRNA'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=other'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=protein-coding'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=pseudo'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=rRNA'  
drwxr-xr-x 2 xdtr104 uic157  5 Aug  4 16:16 'type_of_gene=scRNA'  
drwxr-xr-x 2 xdtr104 uic157  85 Aug  4 16:15 'type_of_gene=snRNA'  
drwxr-xr-x 2 xdtr104 uic157  85 Aug  4 16:16 'type_of_gene=snoRNA'  
drwxr-xr-x 2 xdtr104 uic157  87 Aug  4 16:15 'type_of_gene=tRNA'  
drwxr-xr-x 2 xdtr104 uic157  62 Aug  4 16:16 'type_of_gene=unknown'
```

- They can be partitioned for query efficiency

Example Notebooks

<https://github.com/sbl-sdsc/df-parallel>

Dataframe Library	Parallel	Out-of-core	CPU/GPU
Pandas	no	no [1]	CPU
Dask	yes	yes	CPU
Spark	yes	yes	CPU
cuDF	yes	no	GPU
Dask-cuDF	yes	yes	GPU

[1] Pandas can read data in chunks, but they have to be processed independently.

Task 2

- Compare the runtime of 5 dataframe libraries
- Compare csv vs. parquet files for Cuda dataframe
- Follow the instructions in section 6.2: Task 2
https://github.com/sdsc/sdsc-summer-institute-2022/tree/main/6.2_scaling_up_interactive_data_analysis_jupyter_lab#task-2-run-notebooks-in-jupyter-lab

Dataframe Comparison

Results for running on SDSC [Expanse GPU node](#) with 10 CPU cores (Intel Xeon Gold 6248 2.5 GHz), 1 GPU (NVIDIA V100 SMX2), and 92 GB of memory (DDR4 DRAM), local storage (1.6 TB Samsung PM1745b NVMe PCIe SSD).

Datafile size (gene_info.tsv):

- Dataset 1: 5.4 GB (18 GB in Pandas)
- Dataset 2: 21.4 GB (4 x Dataset 1) (62.4 GB in Pandas)
- Dataset 3: 43.7 GB (8 x Dataset 1)

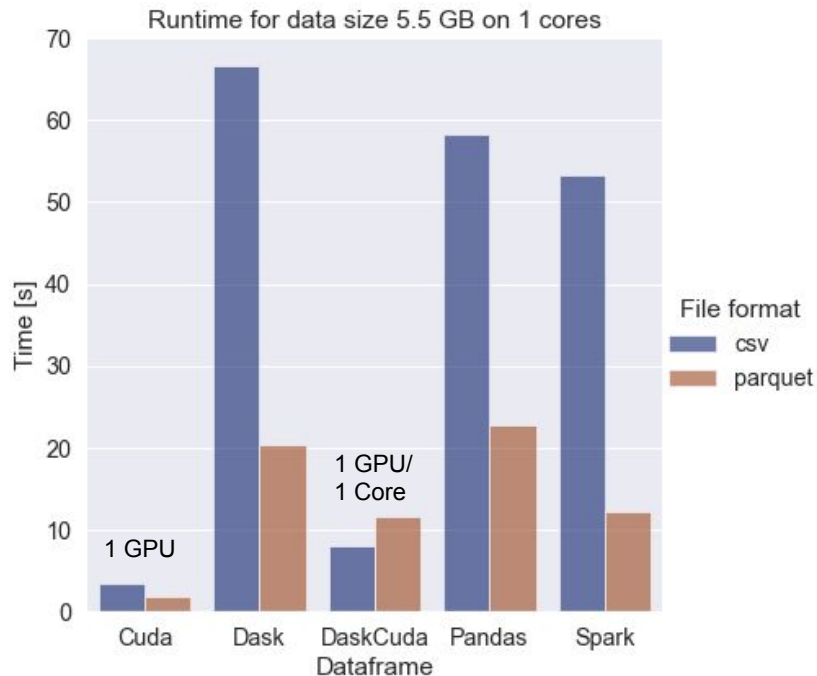
Dataframe Library	time(5.4 GB) (s)	time(21.4 GB) (s)	time(43.7 GB) (s)	Parallel	Out-of-core	CPU/GPU
Pandas	56.3	222.4	-- [2]	no	no	CPU
Dask	15.7	42.1	121.8	yes	yes	CPU
Spark	14.2	31.2	56.5	yes	yes	CPU
cuDF	3.2	-- [2]	-- [2]	yes	no	GPU
Dask-cuDF	7.3	11.9	19.0	yes	yes	GPU

[2] out of memory

Measure Parallel Efficiency

Overall Performance - 1 Core or 1GPU

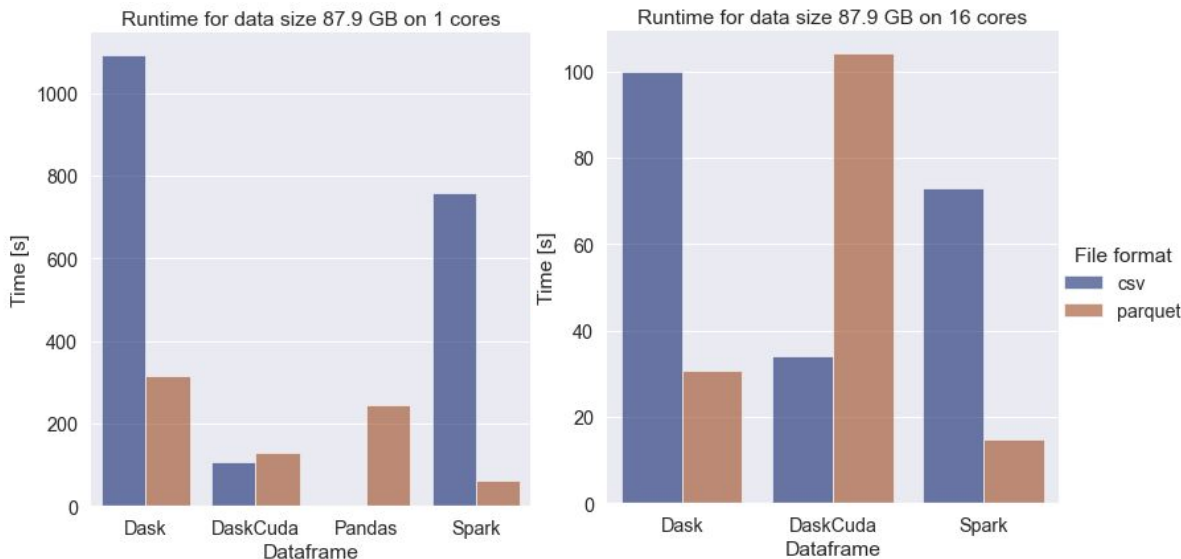
Small Dataset (csv: 5.5 GB, in-memory: 15.2 GB)



- GPU outperforms CPU
- Parquet outperforms CSV file format (except for DaskCuda)
- DaskCuda adds overhead to Cuda

Overall Performance - Large Dataset

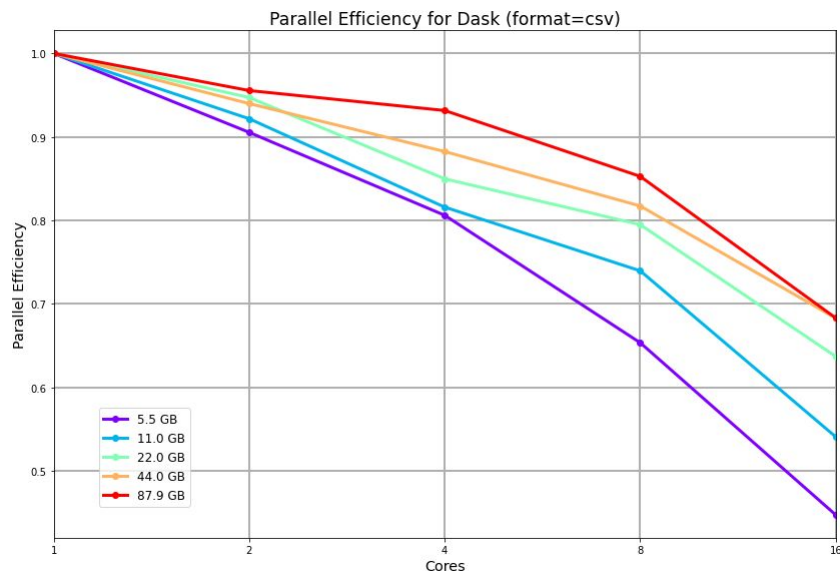
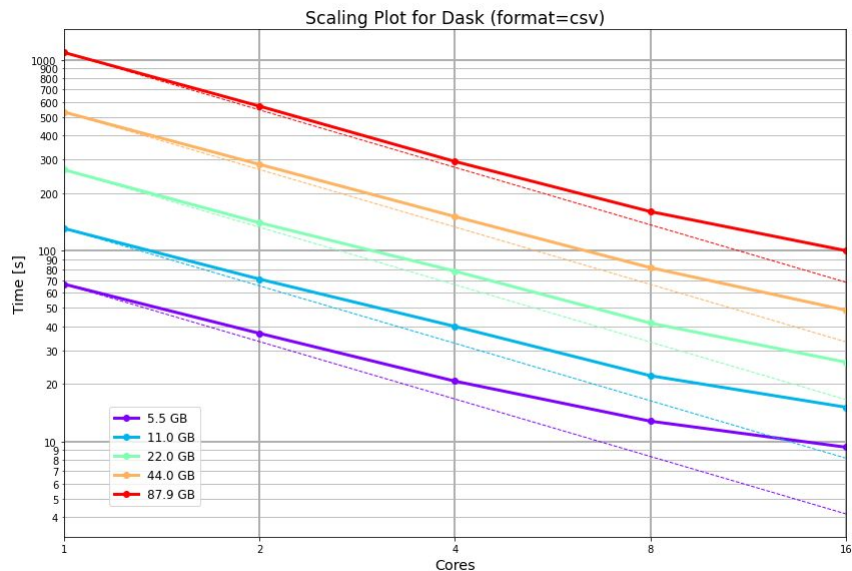
Large Dataset (csv: 87.9 GB) = 16x Small Dataset



- Cuda out of memory error
- Pandas can handle large Parquet files (not CSV)
- Parquet outperforms CSV file format (except for DaskCuda)
- Spark w/ Parquet file has overall best performance

Scaling for Dask Dataframe

Runtime as function of dataset size and number of cores

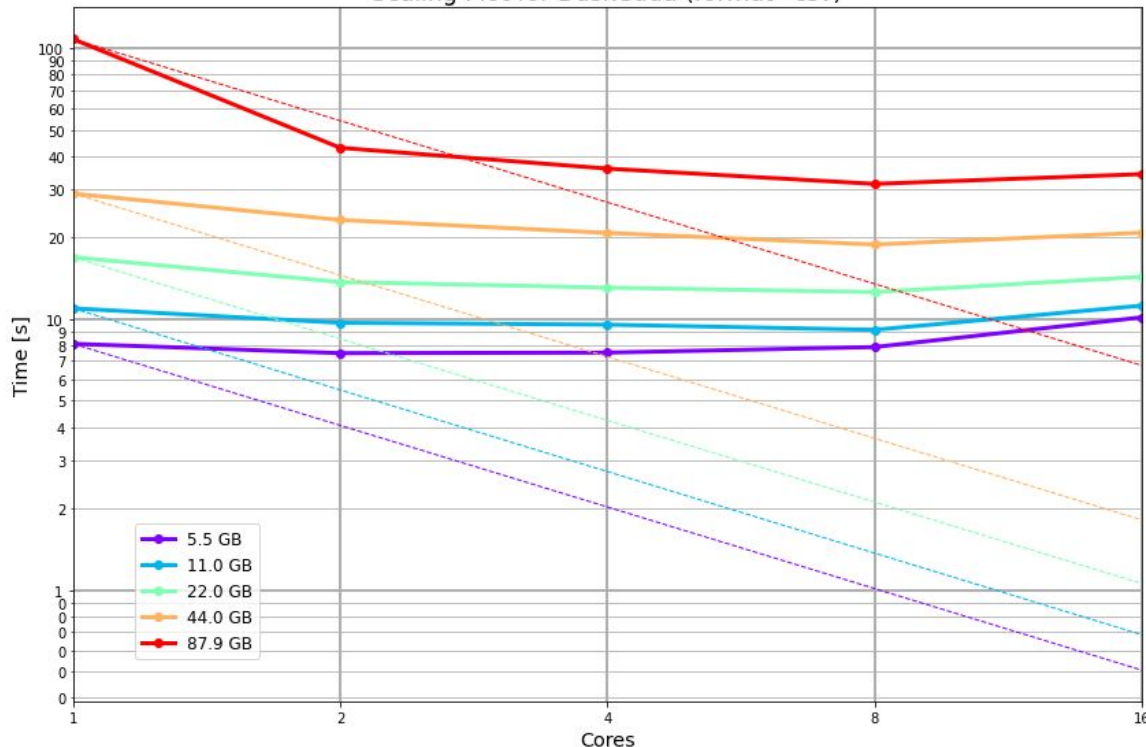


Interactive benchmark: [7-ParallelEfficiency.ipynb](#)

Batch benchmark: slurm script: [benchmark.sb](#) notebook: [8-BenchmarkSummary.ipynb](#)

GPU Dataframe

Scaling Plot for DaskCuda (format=csv)



- DaskCuda can handle large datasets
- Number of CPU cores has little effect, except for the large datasets

How many Cores should I use?

$\text{cost} = \text{core} * \text{time}/\text{size}$

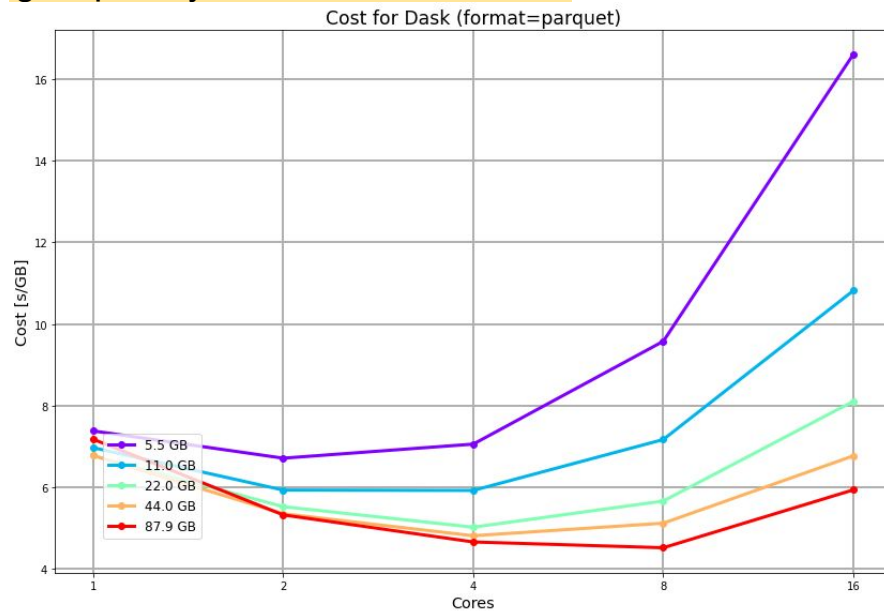
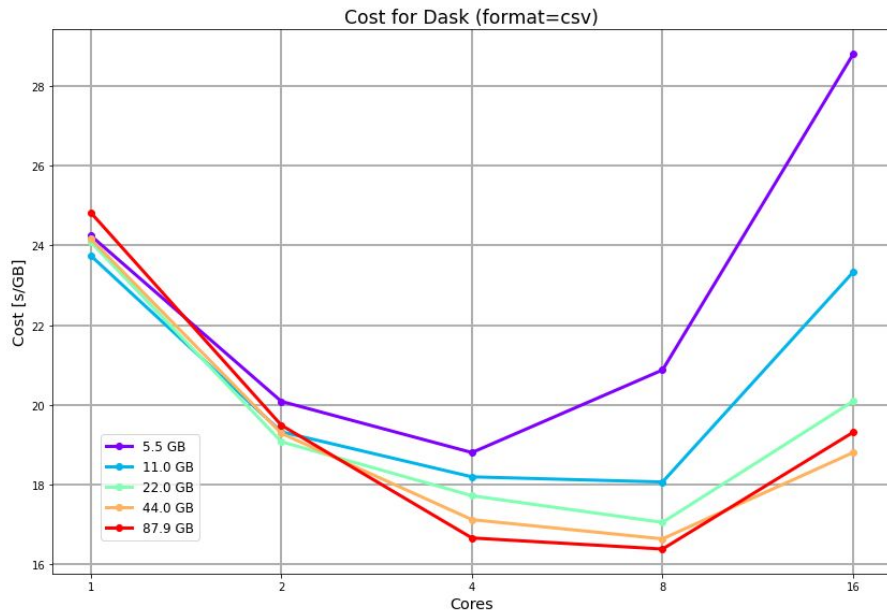
this favors a single core

$\text{opportunity_cost} = 1$

adjustable parameter

$\text{cost} += \text{opportunity_cost} * \text{time}/\text{size}$

give priority to finish task faster



How much does it cost to run the jobs?

Run on CPU (Pandas, Dask, Spark dataframes)

```
galyleo launch --account <account_number> --partition shared --cpus 10  
--memory 20 --time-limit 00:30:00 --conda-env df-parallel  
--conda-yml "${HOME}/df-parallel/environment.yml" --mamba
```

1 CPU or 2GB of memory are charged 1 CPU Service Unit (SU)/hour.
This job will be charged 10 SU/hour or 5 SUs for 30 minutes.

Run on GPU (Pandas, Dask, Spark, cuDF, Dask-cuDF dataframes)

```
galyleo launch --account <account_number> --partition gpu-shared --cpus 10  
--memory 92 --gpus 1 --time-limit 00:30:00 --conda-env df-parallel-gpu  
--conda-yml "${HOME}/df-parallel/environment_gpu.yml" --mamba
```

1 GPU or 10 CPUs or 92 GB of memory are charged 1 GPU Service Unit (SU)/hour.
This job will be charged 1 GPU SU/hour. **The minimum charge for any job is 1 SU.** So
this job will use 1 SU even though it's just run for 30 minutes.

Get ready to use Expanse

Accounts and allocations

Expanse Allocation

- Apply for an Expanse trial allocation or submit a proposal for a larger allocation.
- Using the trial account, run some performance evaluations
- Sept. 1, 2022: The ACCESS Resource Allocations Marketplace and Platform Services (RAMPS) will replace the XSEDE
- Check for updates here:

<https://portal.xsede.org/allocations/announcements>

Summary

- When to run on Expanse
- Setup a portable and reproducible software environment
- Run Jupyter Lab on Expanse
- Scale up calculations on CPU/GPU - Dataframes
- Measure parallel efficiency
- Get ready to use Expanse: accounts, allocations

Homework

- Install df-parallel on your laptop/desktop
- Run the CPU dataframe examples
- Compare the performance with Expanse
- Apply what you've learned to you own work
- Commit yourself to write portable and reproducible code

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CyberTraining: Implementation: Small: Developing a Best Practices Training Program in Cyberinfrastructure-Enabled Machine Learning Research