

HPC-Friendly Workflows in Julia



“Julia + Jupyter + GPU = 🧠 🔥 🧬 😊”
(phrase borrowed from Marius Millea)

Johannes Blaschke
Data Science Engagement Group
NERSC, LBNL

Credit and Disclaimers

None of this would be possible without:

- Tim Bersard, Valentin Churavy, Julian Samaroo (MIT Julia Lab) + Anton Smirnov (AMD) + Carsten Bauer (NHR, PC2)
 - Providing the Infrastructure
- Marius Millea (UC Davis) + Mark Hirsbrunner (LBNL*) + William Godoy, Pedro Valero Lara (OLCF)
 - Inspiring applications
- The Julia for HPC working group
 - <https://github.com/JuliaParallel>
 - Meets monthly on Zoom (cf. <https://julia-lang.org/community/>) and is very active on Discord
 - Julia for HPC BoF at SC and JuliaCon
- Soham Ghosh (NERSC)
 - Exploring AI applications: just-in-time AI, AI for science, UQ

Disclaimer:

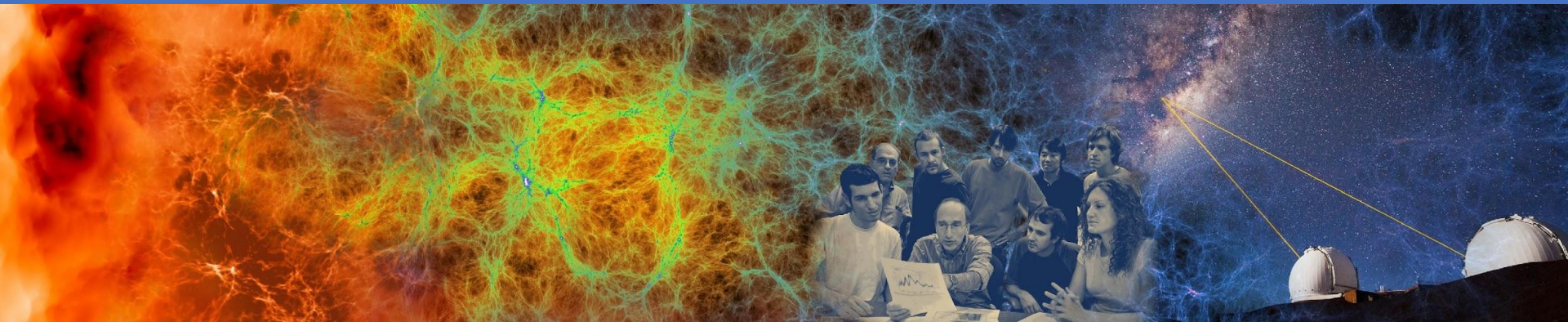
- I work on Perlmutter, but can be (and has been) easily applied to HPC more broadly.



Overview

1. Julia in 60s
2. Julia + Jupyter as an interactive workflow engine
3. Network Discovery
4. Programming GPUs
5. Inspiration: Particles in Potentials
6. Machine Learning using `Flux.jl`
7. Using `Dagger.jl` to parallelize your workflow

Julia in 60s

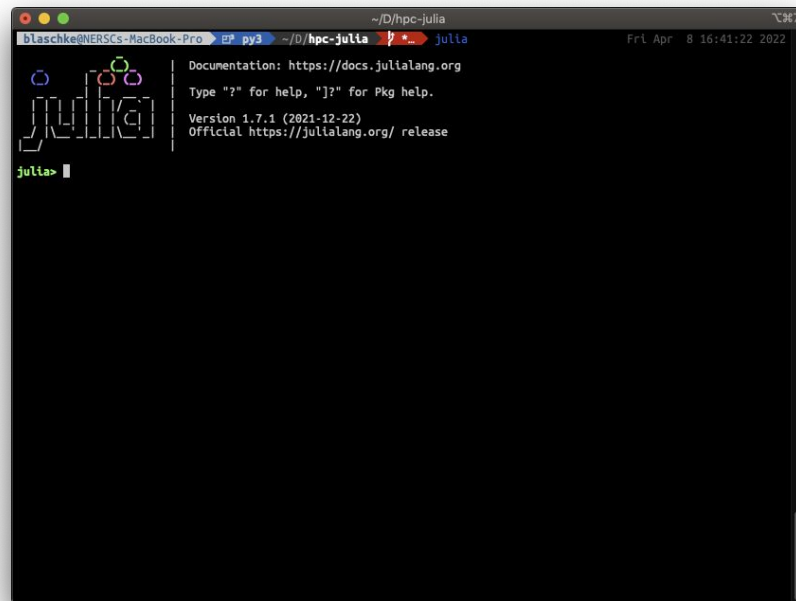


Julia is a High-Productivity Language

- It has all the modern HP features (rich stdlib, gc, ...)

Julia is a High-Productivity Language

- It has all the modern HP features (rich stdlib, gc, ...)
- + a powerful REPL



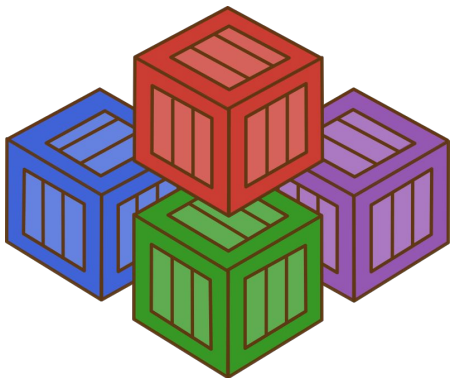
The image shows a terminal window titled "julia" with the following content:

```
blaschke@NERSCs-MacBook-Pro ~/D/hpc-julia julia
Documentation: https://docs.julialang.org
Type "?" for help, "]" for Pkg help.
Version 1.7.1 (2021-12-22)
Official https://julialang.org/ release

julia>
```

Julia is a High-Productivity Language

- It has all the modern HP features (rich stdlib, gc, ...)
- + a powerful REPL
- + a comprehensive package manager (which integrates with system software)



Project.toml:

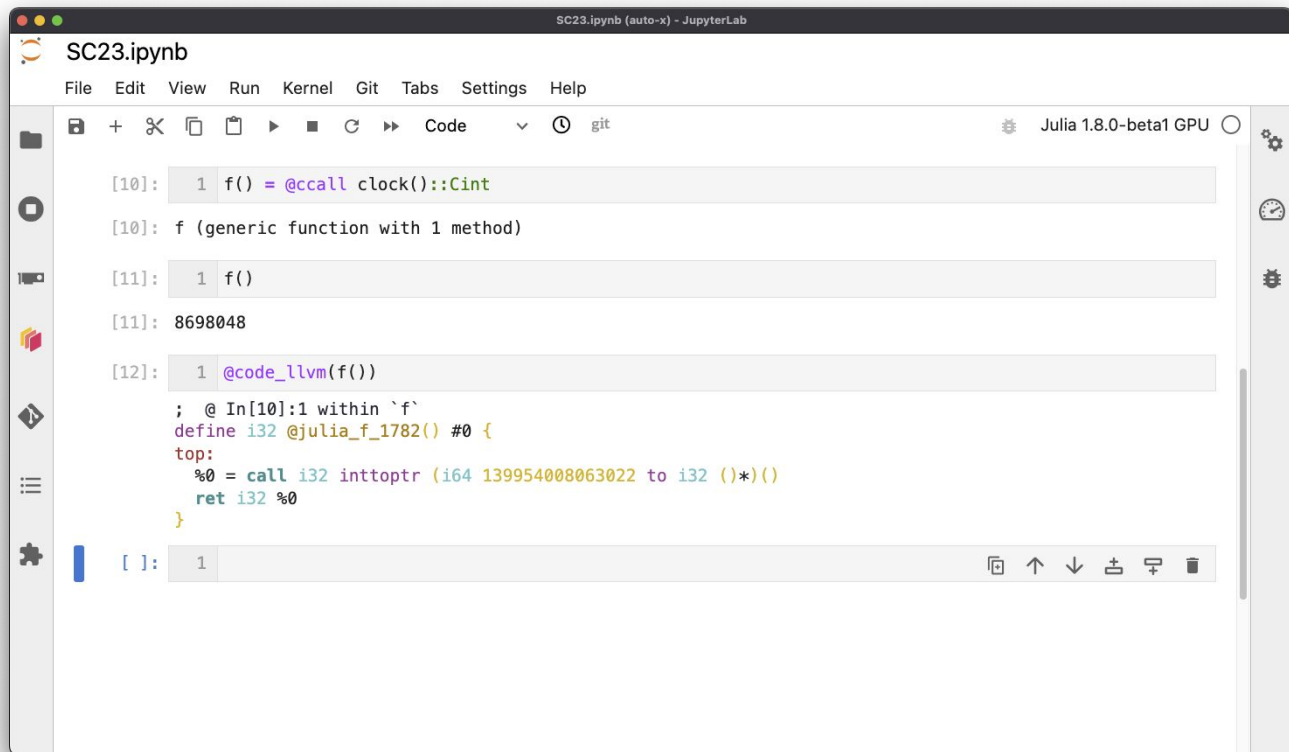
```
[extras]
MPIPreferences = "3da0fdf6-3ccc-4f1b-acd9-58baa6c99267"
CUDA_Runtime_jll = "76a88914-d11a-5bdc-97e0-2f5a05c973a2"
```

LocalPreferences.toml:

```
[MPIPreferences]
_format = "1.1"
abi = "MPICH"
binary = "system"
cclibs = ["cupti", "cudart", "cuda", "sci_gnu_82_mpi", "sci_gnu_82",
"dL", "dsml", "xpmem"]
libmpi = "libmpi_gnu_91.so"
mpiexec = "srun"
preloads = ["libmpi_gtl_cuda.so"]
preloads_env_switch = "MPICH_GPU_SUPPORT_ENABLED"
```

```
[CUDA_Runtime_jll]
local = "true"
version = "11.7"
```

Julia has LLVM under the Hood




The screenshot shows a JupyterLab notebook titled "SC23.ipynb" running Julia 1.8.0-beta1 GPU. The notebook contains the following code and output:

```
[10]: 1 f() = @ccall clock()::Cint
[10]: f (generic function with 1 method)
[11]: 1 f()
[11]: 8698048
[12]: 1 @code_llvm(f())
; @ In[10]:1 within `f`
define i32 @julia_f_1782() #0 {
top:
  %0 = call i32 @inttoptr (i64 139954008063022 to i32 ())*()
  ret i32 %0
}
```


Julia has LLVM under the Hood

Julia data types are
binary-compatible with C

`@ccall` equivalent to `c`
function call



```
SC23.ipynb (auto-x) - JupyterLab

[10]: 1 f() = @ccall clock()::Cint

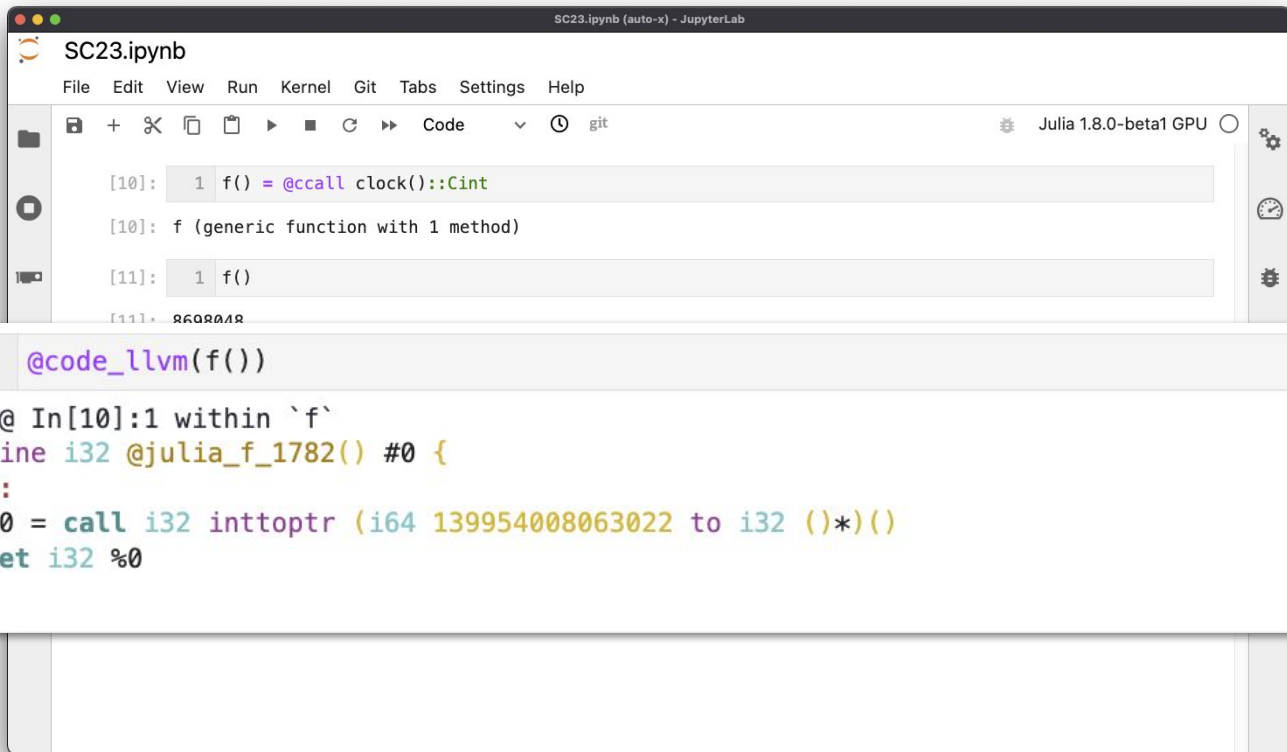
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  ret i32 %0
}
```

Julia has LLVM under the Hood

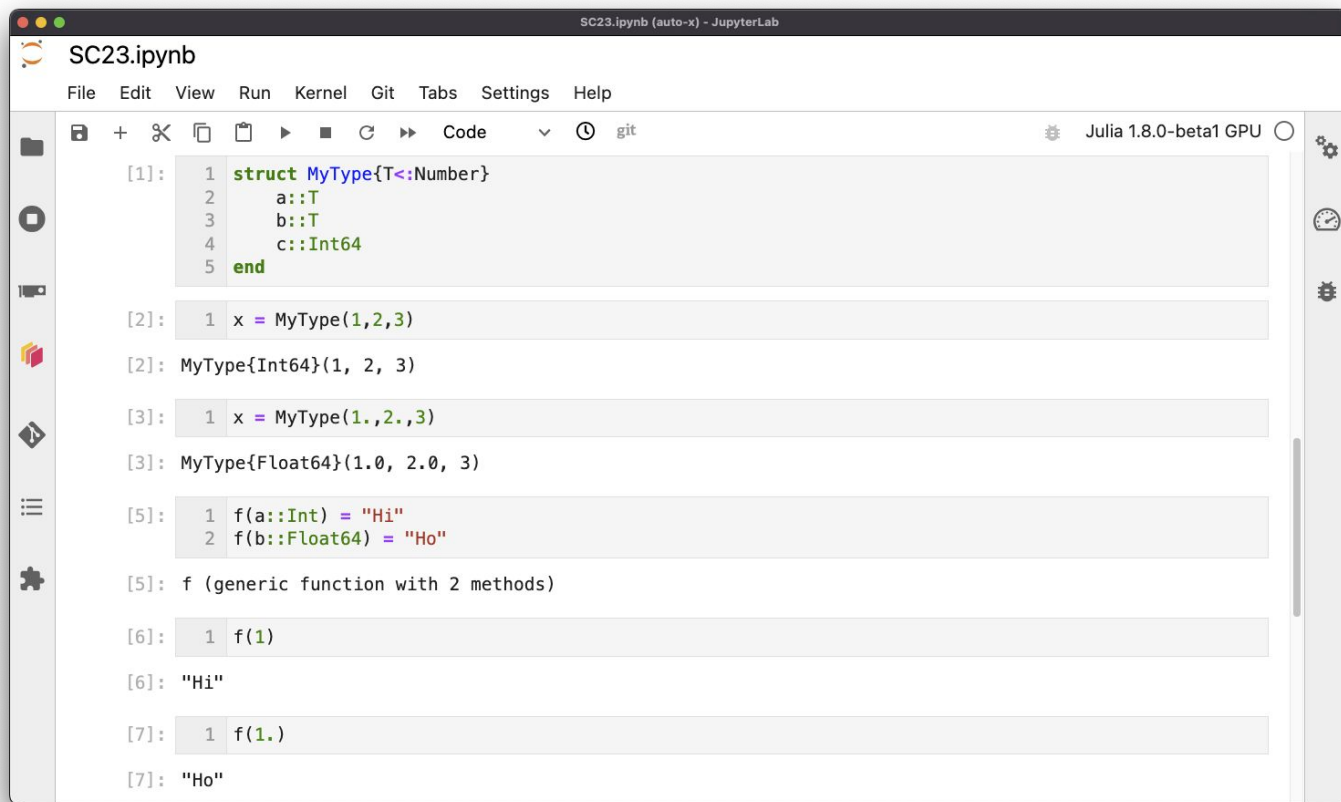


The screenshot shows a JupyterLab notebook titled "SC23.ipynb" with the following content:

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SC23.ipynb (auto-x) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 📄 ▶ ⌂ Code ⌚ git Julia 1.8.0-beta1 GPU ⚙️
[10]: 1 f() = @ccall cclock()::Cint
[10]: f (generic function with 1 method)
[11]: 1 f()
[11]: 8608048
[12]: 1 @code_llvm(f())
; @ In[10]:1 within `f`
define i32 @julia_f_1782() #0 {
top:
    %0 = call i32 @inttoptr (i64 139954008063022 to i32 (*)())
    ret i32 %0
}
```

@code_llvm exposes the LLVM IR for debug purposes

Julia has a Powerful Type System



The screenshot shows a JupyterLab notebook titled "SC23.ipynb" with the following code and output:

```
[1]: 1 struct MyType{T<:Number}
      2     a::T
      3     b::T
      4     c::Int64
      5 end
```

```
[2]: 1 x = MyType(1,2,3)
```

```
[2]: MyType{Int64}(1, 2, 3)
```

```
[3]: 1 x = MyType(1.,2.,3)
```

```
[3]: MyType{Float64}(1.0, 2.0, 3)
```

```
[5]: 1 f(a::Int) = "Hi"
      2 f(b::Float64) = "Ho"
```

```
[5]: f (generic function with 2 methods)
```

```
[6]: 1 f(1)
```

```
[6]: "Hi"
```

```
[7]: 1 f(1.)
```

```
[7]: "Ho"
```

Julia has a Powerful Type System

Structured data types are also compatible with C

`{T<:Number}` represents a type template for all types inheriting from `Number`

```
SC23.ipynb (auto-x) - JupyterLab
[1]: 1 struct MyType{T<:Number}
      2     a::T
      3     b::T
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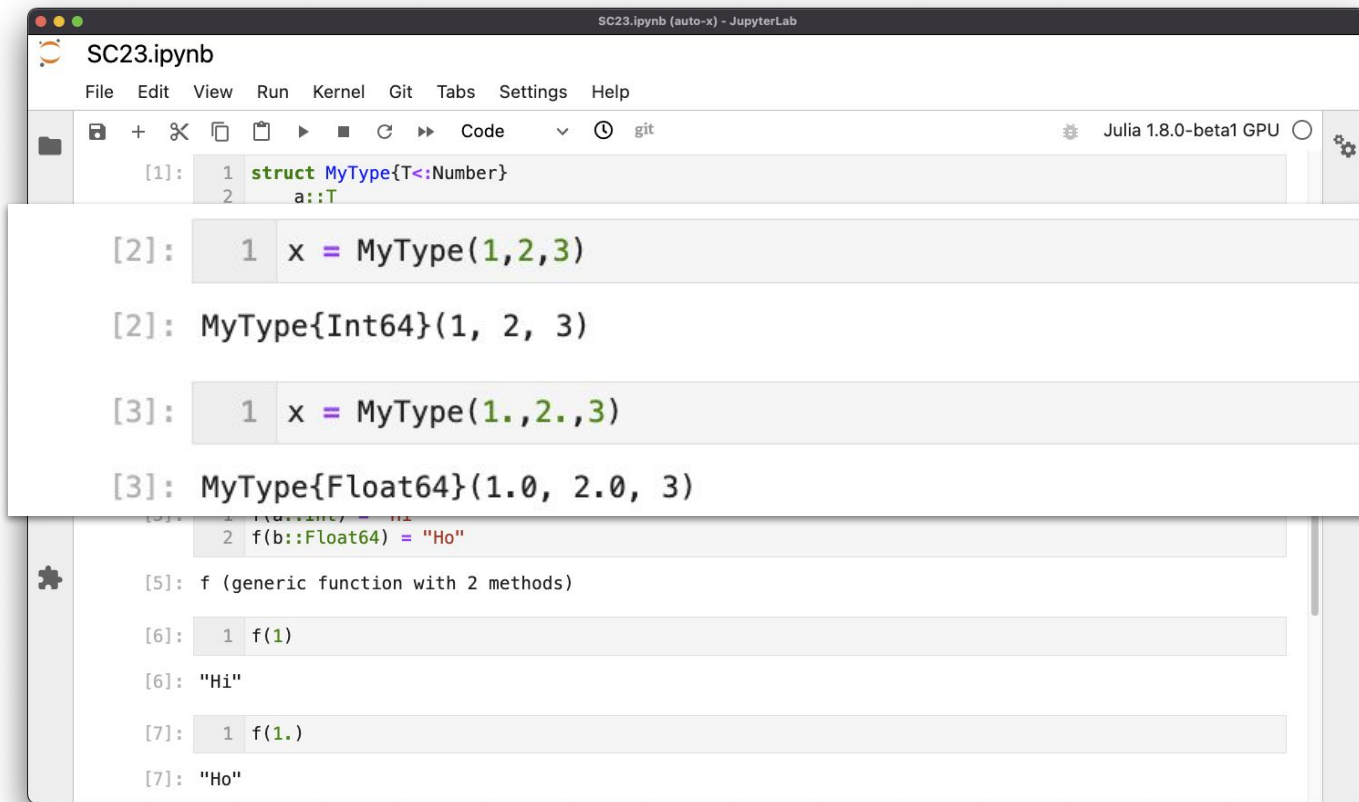
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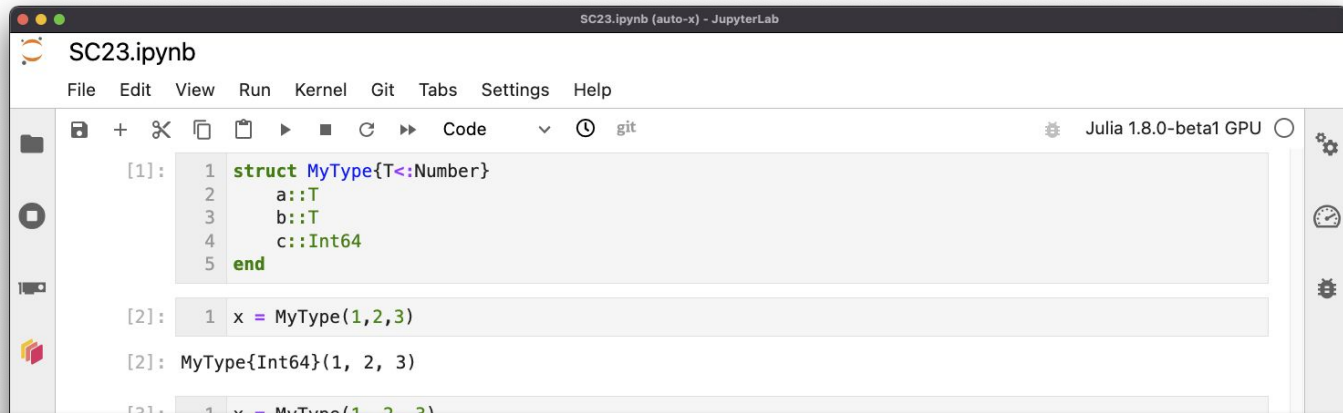
Julia has a Powerful Type System

`{T<:Number}` represents a type template for all types inheriting from `Number`



```
SC23.ipynb (auto-x) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ - X Copy Paste Run Code git Julia 1.8.0-beta1 GPU
[1]: 1 struct MyType{T<:Number}
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[2]: 1 x = MyType(1,2,3)
[2]: MyType{Int64}(1, 2, 3)
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Julia has a Powerful Type System



```
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File Edit View Run Kernel Git Tabs Settings Help
Code git Julia 1.8.0-beta1 GPU
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3     b::T
4     c::Int64
5 end
[2]: 1 x = MyType(1,2,3)
[2]: MyType{Int64}(1, 2, 3)
```

```
[5]: 1 f(a::Int) = "Hi"
2     f(b::Float64) = "Ho"
```

[5]: f (generic function with 2 methods)

```
[6]: 1 f(1)
```

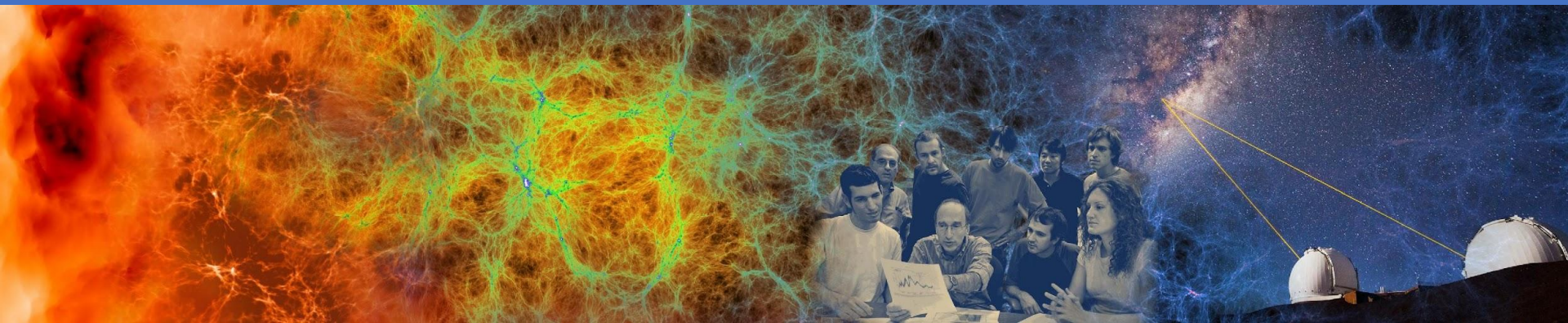
[6]: "Hi"

```
[7]: 1 f(1.)
```

[7]: "Ho"

Julia has multiple dispatch:
a function can have several
implementations (methods)
depending on the input
types

Julia + Jupyter as an interactive workflow engine



DOE SC User Requirements Are Evolving



IRI Science Patterns (3)

Time-sensitive pattern has *urgency*, requiring real-time or end-to-end performance with high reliability, e.g., for timely decision-making, experiment steering, and virtual proximity.

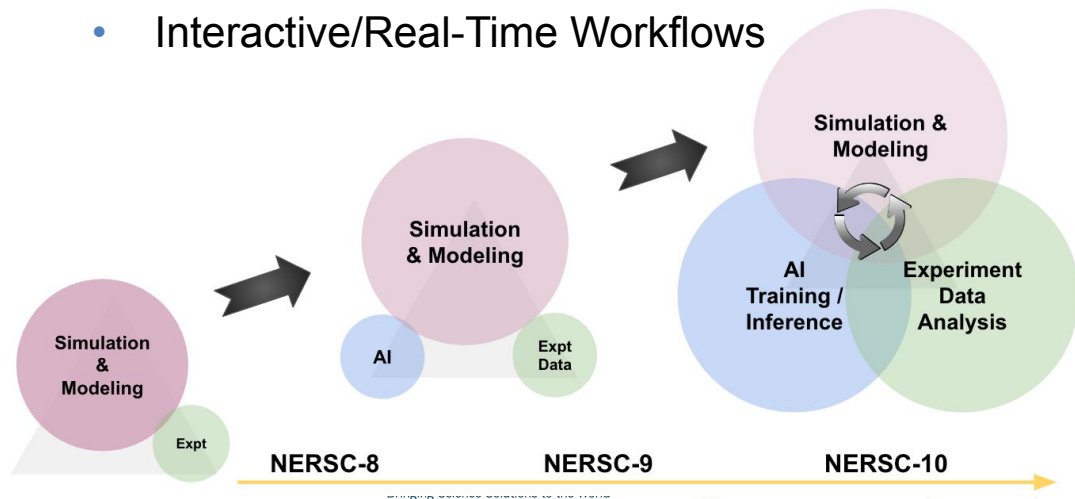
Data integration-intensive pattern requires combining and analyzing data from multiple sources, e.g., sites, experiments, and/or computational runs.

Long-term campaign pattern requires sustained access to resources over a long period to accomplish a well-defined objective.



Users require support for

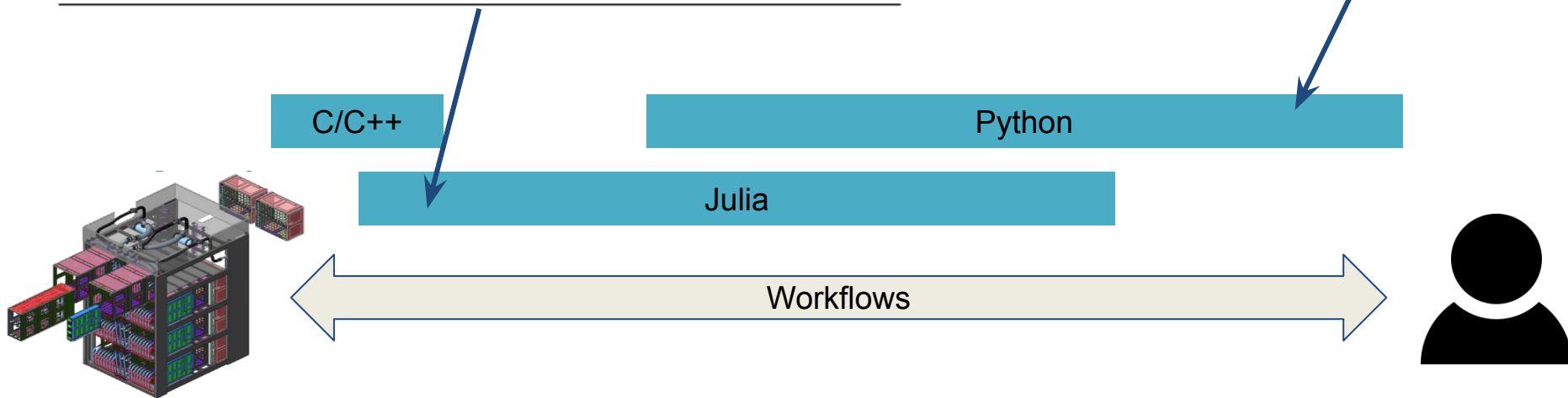
- End-to-end DOE SC Workflows involving multiple facilities
- New modes of scientific discovery through the integration of simulation & modeling, AI and experiment.
- Interactive/Real-Time Workflows



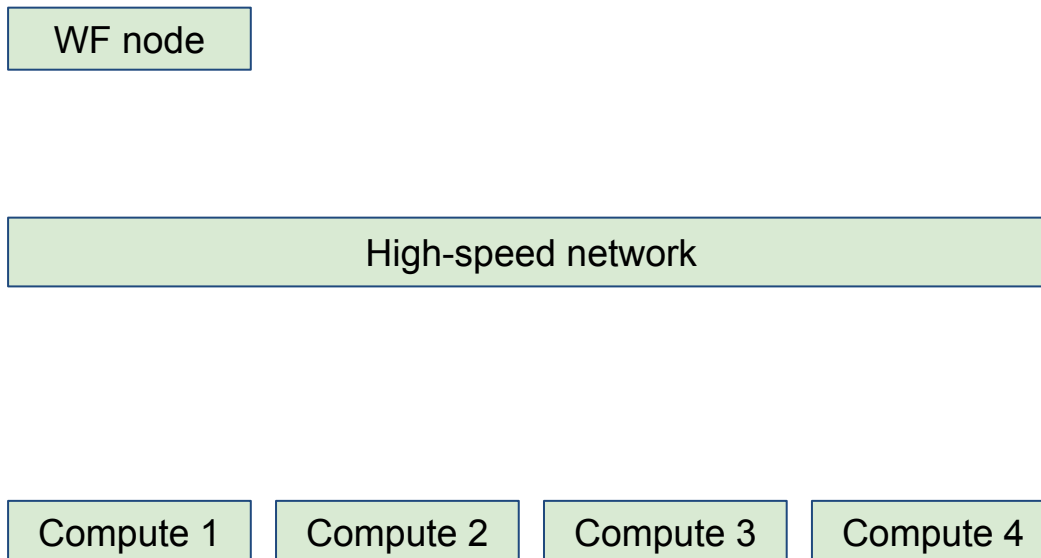
Why NERSC Cares about Julia Workflows

Function signature	Pybind11	ccall	speedup
int fn0()	132 ±14.9	2.34 ±1.24	56×
int fn1(int)	217 ±20.9	2.35 ±1.33	92×
double fn2(int, double)	232 ±11.7	2.32 ±0.189	100×
char* fn3(int, double, char*)	267 ±28.9	6.27 ±0.396	42×

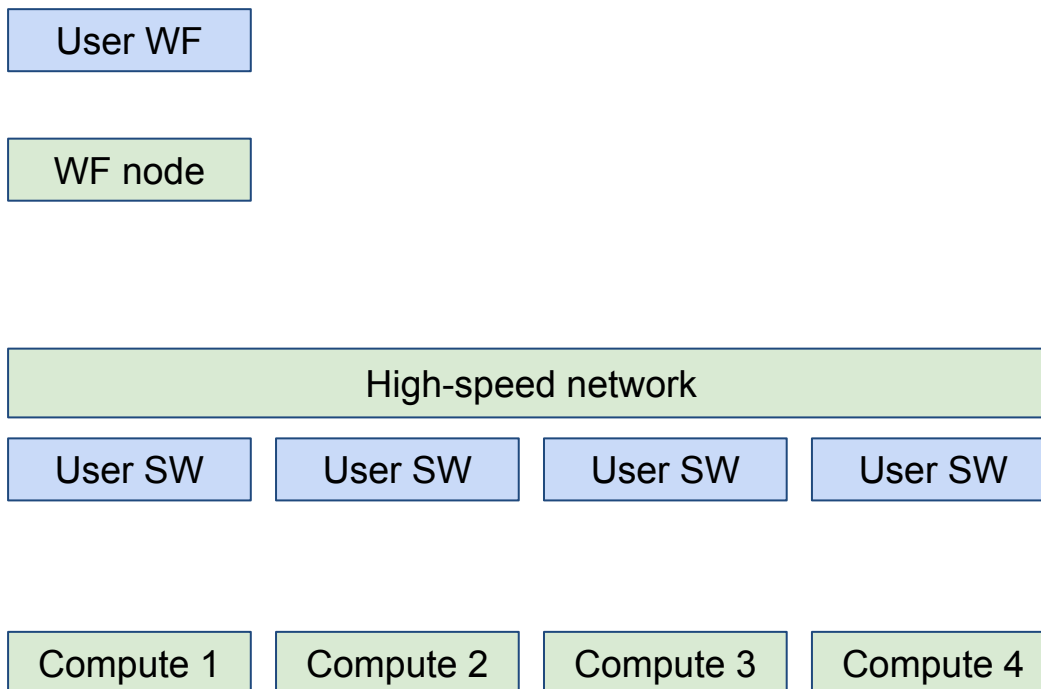
pip install ...
Rapid scripting



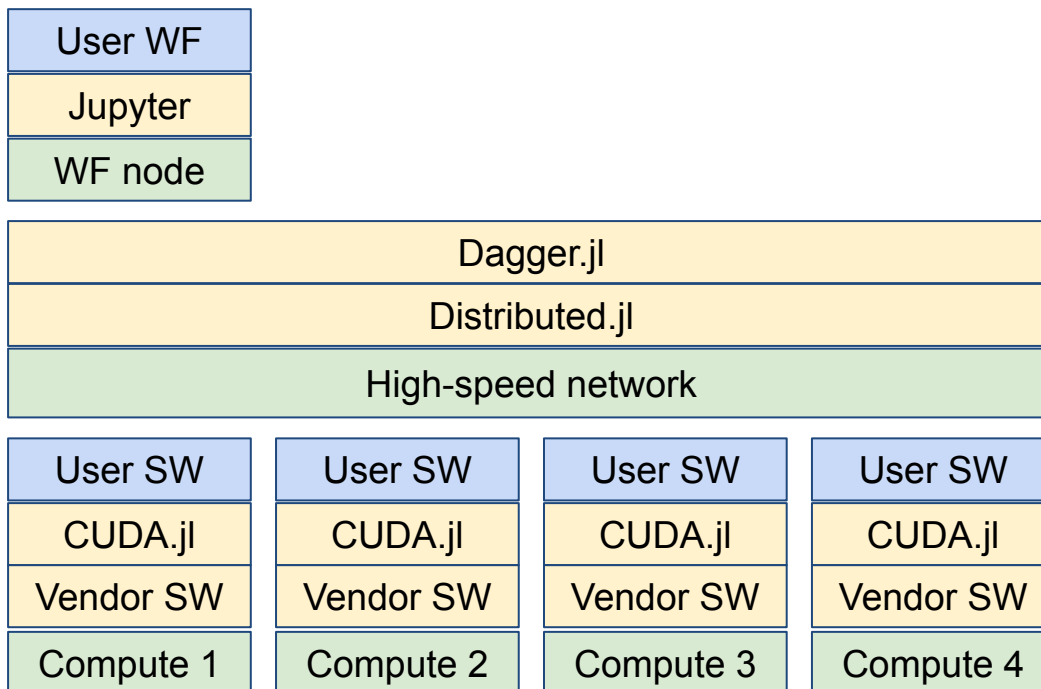
Building a Distributed Julia Application (without MPI)



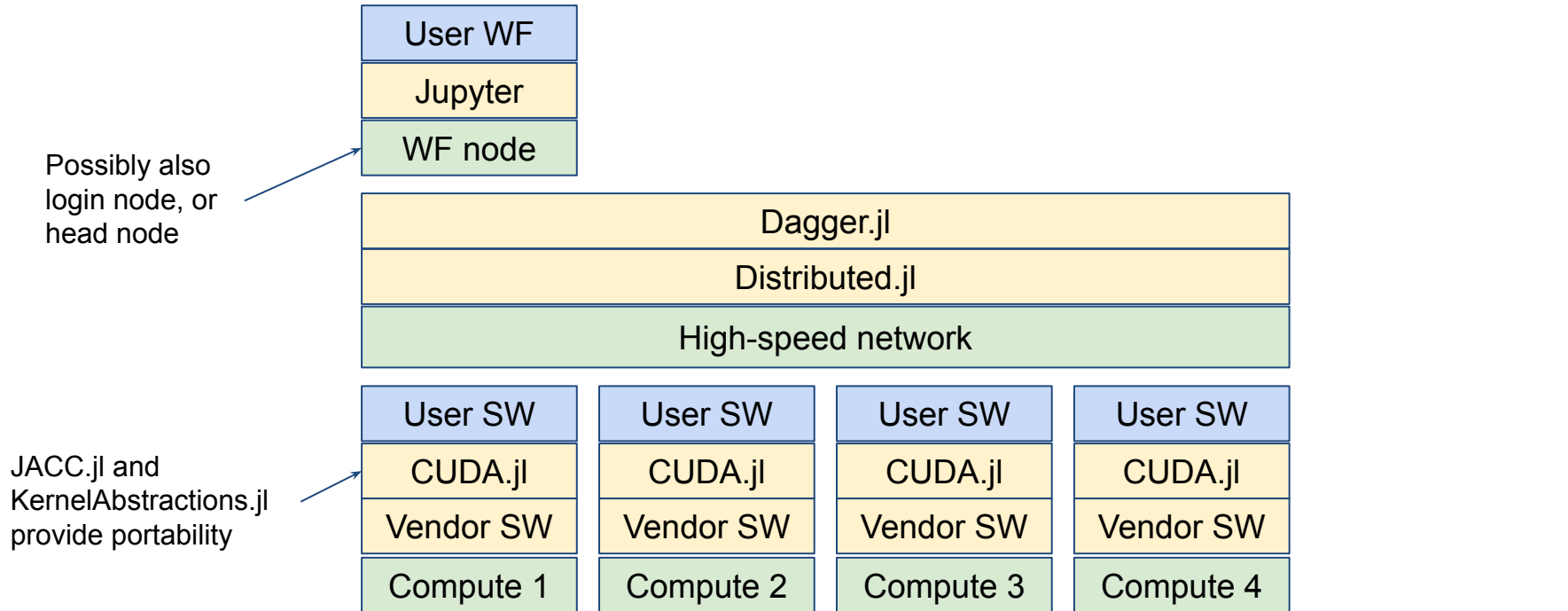
Building a Distributed Julia Application (without MPI)



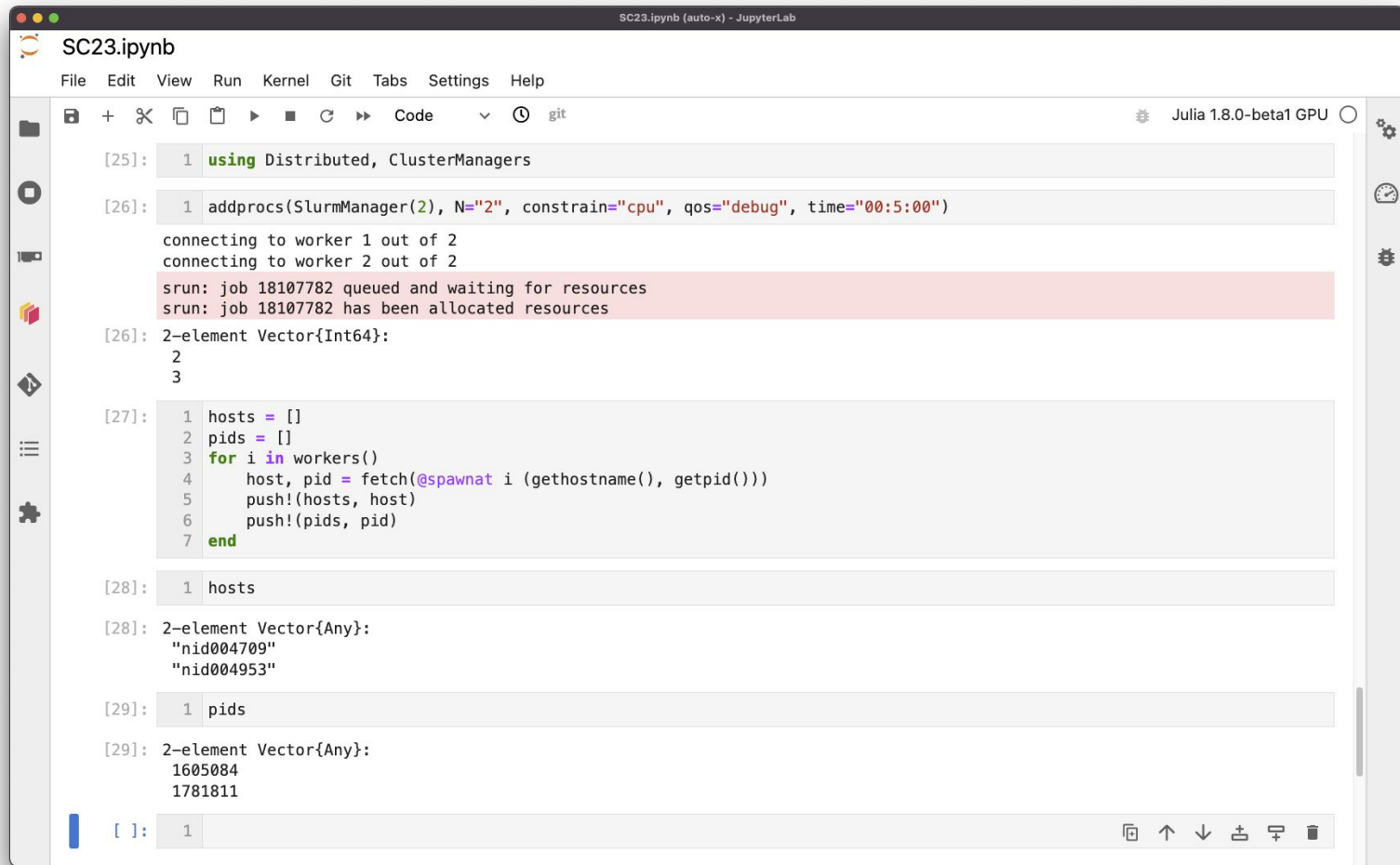
Building a Distributed Julia Application (without MPI)



Building a Distributed Julia Application (without MPI)



Cluster Managers: Interaction with Slurm



```
SC23.ipynb
File Edit View Run Kernel Git Tabs Settings Help
[25]: 1 using Distributed, ClusterManagers
[26]: 1 addprocs(SlurmManager(2), N="2", constrain="cpu", qos="debug", time="00:5:00")
      connecting to worker 1 out of 2
      connecting to worker 2 out of 2
      srun: job 18107782 queued and waiting for resources
      srun: job 18107782 has been allocated resources
[26]: 2-element Vector{Int64}:
      2
      3
[27]: 1 hosts = []
      2 pids = []
      3 for i in workers()
      4     host, pid = fetch(@spawnat i (gethostname(), getpid()))
      5     push!(hosts, host)
      6     push!(pids, pid)
      7 end
[28]: 1 hosts
[28]: 2-element Vector{Any}:
      "nid004709"
      "nid004953"
[29]: 1 pids
[29]: 2-element Vector{Any}:
      1605084
      1781811
[ ]: 1
```

Cluster Managers: Interaction with Slurm

Request two
cpu nodes

```
[26]: 1 addprocs(SlurmManager(2), N="2", constrain="cpu", qos="debug", time="00:5:00")
      connecting to worker 1 out of 2
      connecting to worker 2 out of 2
      srun: job 18107782 queued and waiting for resources
      srun: job 18107782 has been allocated resources
```

ElasticManager
can be used instead
of SlurmManager
to manually manage
workers from *within*
an allocation

```
[27]: 1 hosts = []
      2 pids = []
      3 for i in workers()
      4     host, pid = fetch(@spawnat i (gethostname(), getpid()))
      5     push!(hosts, host)
      6     push!(pids, pid)
      7 end
```

```
[28]: 1 hosts
```

```
[28]: 2-element Vector{Any}:
      "nid004709"
      "nid004953"
```

```
[29]: 1 pids
```

```
[29]: 2-element Vector{Any}:
      1605084
      1781811
```

```
[ ]: 1
```



Cluster Managers: Interaction with Slurm

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SC23.ipynb
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[25]: 1 using Distributed, ClusterManagers
[26]: 1 addprocs(SlurmManager(2), N="2", constrain="cpu", qos="debug", time="00:5:00")
      connecting to worker 1 out of 2
      connecting to worker 2 out of 2
```

Get hostnames
and pids from
each worker

```
[27]: 1 hosts = []
      2 pids = []
      3 for i in workers()
      4     host, pid = fetch(@spawnat i (gethostname(), getpid()))
      5     push!(hosts, host)
      6     push!(pids, pid)
      7 end
```

```
[28]: 2-element Vector{Any}:
      "nid004709"
      "nid004953"
```

```
[29]: 1 pids
```

```
[29]: 2-element Vector{Any}:
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```

```
[ ]: 1
```



Cluster Managers: Interaction with Slurm

```
SC23.ipynb
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 📄 ▶ ■ 🔄 ▶▶ Code ⌵ ⌚ git Julia 1.8.0-beta1 GPU ⚙️
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```
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      "nid004709"
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```

```
[29]: 1 pids
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```
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      1605084
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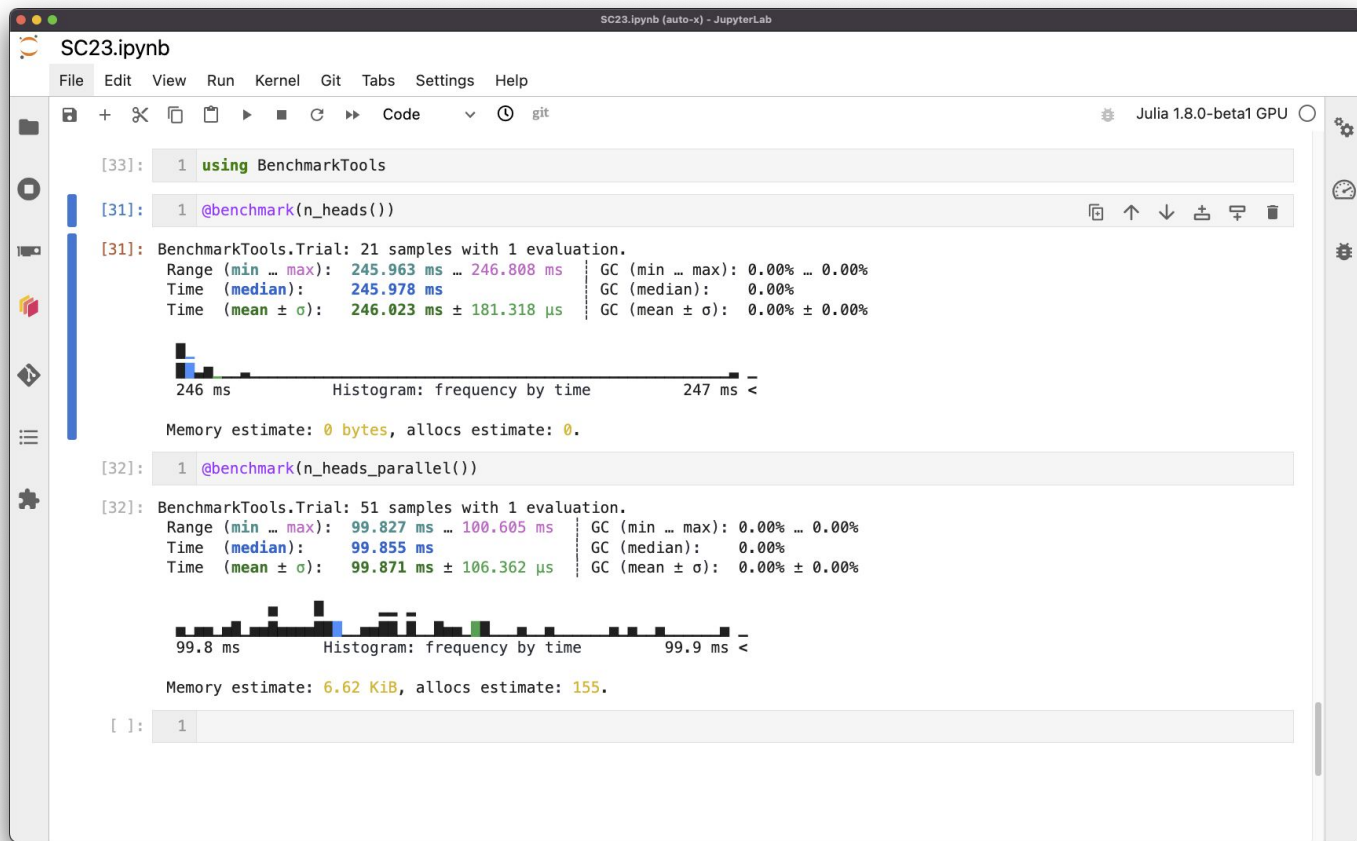
Distributed.jl supports basic workflows

Basic task: count number of heads from 2×10^8 fair coin tosses.

- Serial implementation:
for loop + increment counter
- Parallel (distributed) implementation:
@distributed for loop + reduction
(summation) on counter
- Most Julia data types are trivial to
serialize and communicate over network
(the users doesn't have to do anything
"special" to enable this)

```
1 function n_heads()  
2     n = 0  
3     for i = 1:200000000  
4         n += Int(rand(Bool))  
5     end  
6     n  
7 end  
8  
9 function n_heads_parallel()  
10    nheads = @distributed (+) for i = 1:200000000  
11        Int(rand(Bool))  
12    end  
13    nheads  
14 end
```

Performance Gains from Distributing Work



The screenshot shows a JupyterLab notebook titled "SC23.ipynb" with the following content:

```
[33]: 1 using BenchmarkTools
```

```
[31]: 1 @benchmark(n_heads())
```

```
[31]: BenchmarkTools.Trial: 21 samples with 1 evaluation.  
Range (min ... max): 245.963 ms ... 246.808 ms | GC (min ... max): 0.00% ... 0.00%  
Time (median): 245.978 ms | GC (median): 0.00%  
Time (mean ± σ): 246.023 ms ± 181.318 μs | GC (mean ± σ): 0.00% ± 0.00%
```

Histogram: frequency by time

Memory estimate: 0 bytes, allocs estimate: 0.

```
[32]: 1 @benchmark(n_heads_parallel())
```

```
[32]: BenchmarkTools.Trial: 51 samples with 1 evaluation.  
Range (min ... max): 99.827 ms ... 100.605 ms | GC (min ... max): 0.00% ... 0.00%  
Time (median): 99.855 ms | GC (median): 0.00%  
Time (mean ± σ): 99.871 ms ± 106.362 μs | GC (mean ± σ): 0.00% ± 0.00%
```

Histogram: frequency by time

Memory estimate: 6.62 KiB, allocs estimate: 155.

```
[ ]: 1
```

Performance Gains from Distributing Work

```
SC23.ipynb
File Edit View Run Kernel Git Tabs Settings Help
Julia 1.8.0-beta1 GPU1

[31]: 1 @benchmark(n_heads())

[31]: BenchmarkTools.Trial: 21 samples with 1 evaluation.
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Histogram: frequency by time
246 ms 247 ms <

Memory estimate: 0 bytes, allocs estimate: 0.

Time (mean ± σ): 99.871 ms ± 106.362 μs | GC (mean ± σ): 0.00% ± 0.00%

Histogram: frequency by time
99.8 ms 99.9 ms <

Memory estimate: 6.62 KiB, allocs estimate: 155.

[ ]: 1
```

Performance Gains from Distributing Work

Distributing work over 2 nodes results in a 2x performance increase

```
SC23.ipynb
File Edit View Run Kernel Git Tabs Settings Help
+ 🔍 🗑️ ▶️ ⏪ ⏩ Code ⌚ git Julia 1.8.0-beta1 GPU
[33]: 1 using BenchmarkTools
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```

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```



Memory estimate: 6.62 KiB, allocs estimate: 155.

Tangent: Hybrid CPU/GPU Jobs

```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ 🔍 📄 📄 ▶ ⏪ ⏩ Code ⌚ git SC23 Julia 1.9.3 ⚙️ ⚙️ ⚙️
[2]: using Distributed, ClusterManagers

[3]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
srun: job 18134163 queued and waiting for resources
srun: job 18134163 has been allocated resources
connecting to worker 2 out of 2
[3]: 2-element Vector{Int64}:
 2
 3

[4]: addprocs(SlurmManager(2), N="2", constrain="gpu", qos="interactive", time="00:15:00", A="nstaff_g")
connecting to worker 1 out of 2
srun: job 18134168 queued and waiting for resources
srun: job 18134168 has been allocated resources
connecting to worker 2 out of 2
[4]: 2-element Vector{Int64}:
 4
 5
...

[48]: features = []
for i in workers()
    scontrol = fetch(@spawnat i get_features())
    push!(features, scontrol)
end

[49]: features

[49]: 4-element Vector{Any}:
 "ActiveFeatures=cpu,milan,ss11"
 "ActiveFeatures=cpu,milan,ss11"
 "ActiveFeatures=gpu,ss11,a100,hbm40g"
 "ActiveFeatures=gpu,ss11,a100,hbm40g"

[ ]:
```



Tangent: Hybrid CPU/GPU Jobs

```
[3]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
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```
connecting to worker 1 out of 2
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srun: job 18134163 has been allocated resources
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```
connecting to worker 2 out of 2
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```
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```

```
2
```

```
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```

```
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4
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```
5
```

```
...
```

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```
[49]: features
```

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Tangent: Hybrid CPU/GPU Jobs

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SC23.ipynb
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 📄 ▶ ■ ↺ ⏪ Code git SC23 Julia 1.9.3
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```

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```
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```

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```
4
```

```
5
```

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[48]: features = []
for i in workers()
    scontrol = fetch(@spawnat i get_features())
    push!(features, scontrol)
end
```

```
[49]: features
```

```
[49]: 4-element Vector{Any}:
"ActiveFeatures=cpu,milan,ss11"
"ActiveFeatures=cpu,milan,ss11"
"ActiveFeatures=gpu,ss11,a100,hbm40g"
"ActiveFeatures=gpu,ss11,a100,hbm40g"
```


Tangent: Hybrid CPU/GPU Jobs

```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
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[2]: using Distributed, ClusterManagers

[3]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
srun: job 18134163 queued and waiting for resources
srun: job 18134163 has been allocated resources
connecting to worker 2 out of 2
[3]: 2-element Vector{Int64}:
 2
 3

[4]: addprocs(SlurmManager(2), N="2", constrain="gpu", qos="interactive", time="00:15:00", A="nstaff_g")
connecting to worker 1 out of 2
srun: job 18134168 queued and waiting for resources
srun: job 18134168 has been allocated resources
connecting to worker 2 out of 2
```

```
[48]: features = []
      for i in workers()
        scontrol = fetch(@spawnat i get_features())
        push!(features, scontrol)
      end
```

```
[49]: 4-element Vector{Any}:
       "ActiveFeatures=cpu,milan,ss11"
       "ActiveFeatures=cpu,milan,ss11"
       "ActiveFeatures=gpu,ss11,a100,hbm40g"
       "ActiveFeatures=gpu,ss11,a100,hbm40g"

[ ]:
```



Tangent: Hybrid CPU/GPU Jobs

```
SC23.ipynb (11) - JupyterLab
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[2]: using Distributed, ClusterManagers

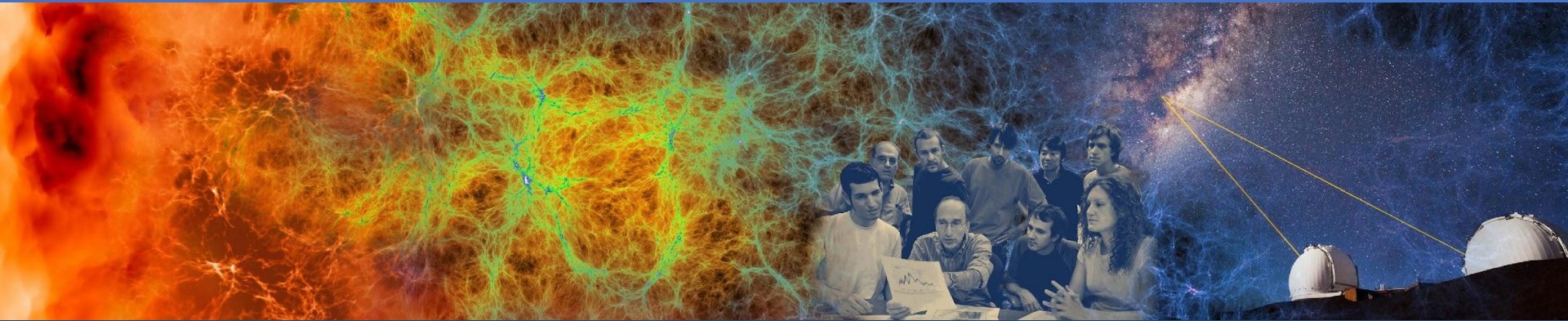
[3]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
srun: job 18134163 queued and waiting for resources
srun: job 18134163 has been allocated resources
connecting to worker 2 out of 2
[3]: 2-element Vector{Int64}:
 2
 3

[4]: addprocs(SlurmManager(2), N="2", constrain="gpu", qos="interactive", time="00:15:00", A="nstaff_g")
connecting to worker 1 out of 2
srun: job 18134168 queued and waiting for resources
srun: job 18134168 has been allocated resources
connecting to worker 2 out of 2
[4]: 2-element Vector{Int64}:
 4
 5
...
```

[49]: features

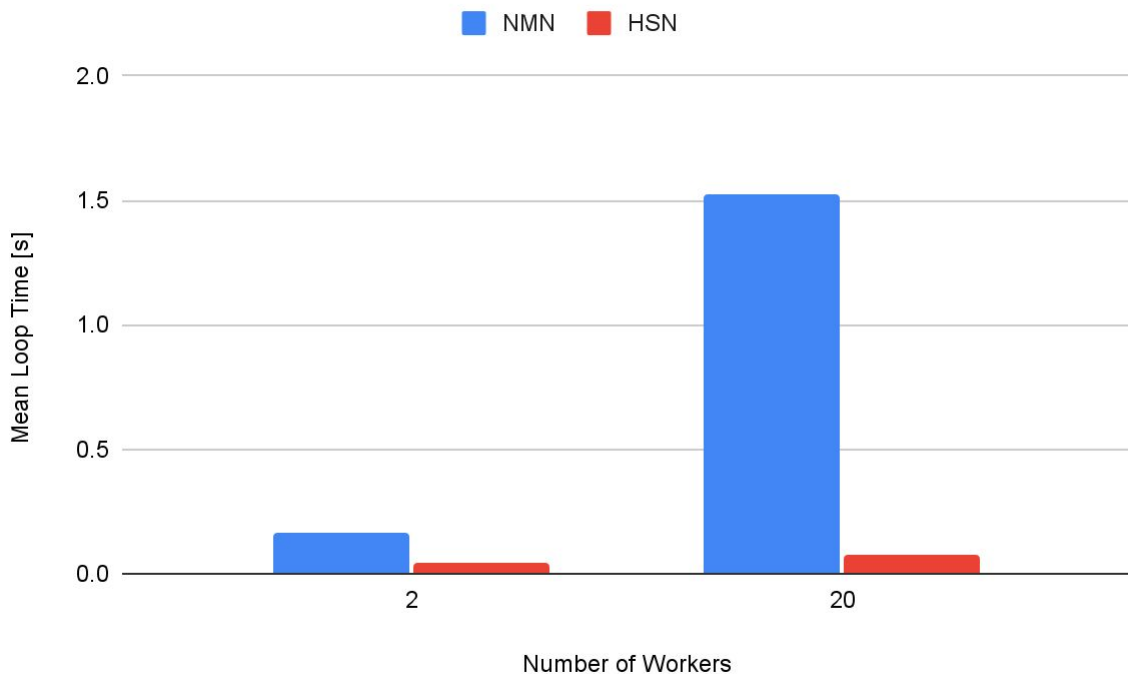
```
[49]: 4-element Vector{Any}:
 "ActiveFeatures=cpu,milan,ss11"
 "ActiveFeatures=cpu,milan,ss11"
 "ActiveFeatures=gpu,ss11,a100,hbm40g"
 "ActiveFeatures=gpu,ss11,a100,hbm40g"
```

Tangent: Network Discovery



Workflow Support Story

- Unexpected poor performance and scaling
- User application 100x slower on Perlmutter

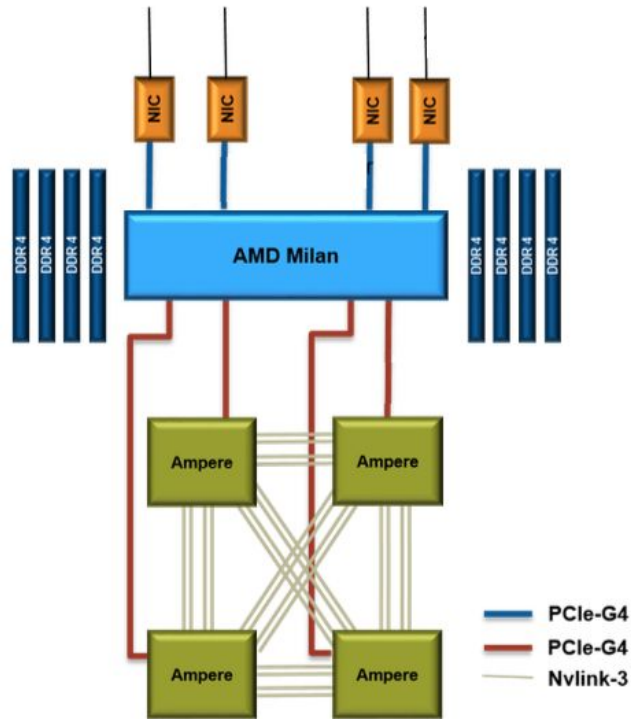


Perlmutter is a Heterogeneous System

Partition	Nodes	CPU	RAM	GPU	NIC
GPU	1536	1x AMD EPYC 7763	256GB	4x NVIDIA A100 (40GB)	4x HPE Slingshot 11
	256	1x AMD EPYC 7763	256GB	4x NVIDIA A100 (80GB)	4x HPE Slingshot 11
CPU	3072	2x AMD EPYC 7763	512GB	–	1x HPE Slingshot 11
Login	40	1x AMD EPYC 7713	512GB	4x NVIDIA A100 (40GB)	–
Large Memory	4	1x AMD EPYC 7713	1TB	4x NVIDIA A100 (40GB)	1x HPE Slingshot 11

- Each GPU node has 4 NICs
 - 1 NIC and 1 GPU per host bridge
- Each CPU node has 1 NIC

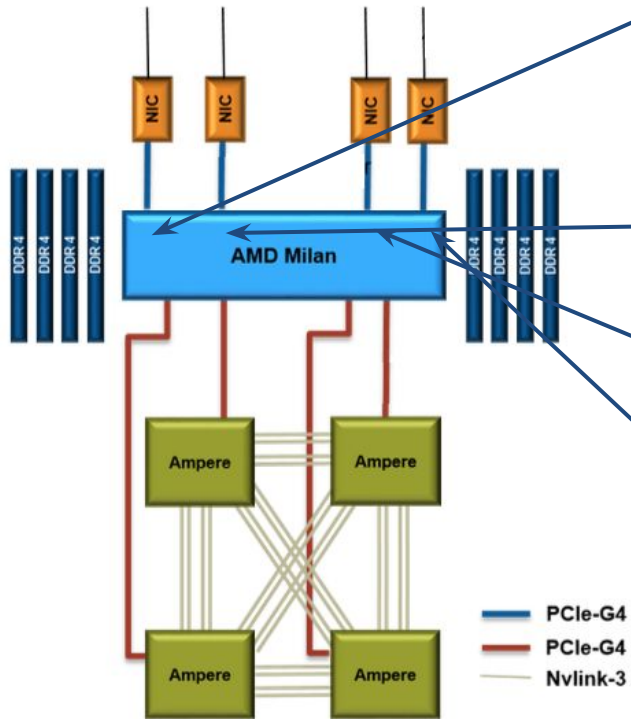
Eg. GPU Node Topology



Hwloc.Object: Machine

```
└─ Hwloc.Object: Package [L#0 P#0]
  └─ Hwloc.Object: Group
    └─ Hwloc.Object: NUMANode
      └─ Hwloc.Object: Bridge [HostBridge]
        └─ Hwloc.Object: Bridge [PCIBridge]
          └─ Hwloc.Object: PCI_Device [c2:00.0 (Ethernet)]
            └─ Hwloc.Object: OS_Device [Net "hsn0"]
        └─ Hwloc.Object: Bridge [PCIBridge]
          └─ Hwloc.Object: PCI_Device [c3:00.0 (Ethernet)]
            └─ Hwloc.Object: OS_Device [Net "hmn0"]
      ...
    └─ Hwloc.Object: Group
      └─ Hwloc.Object: NUMANode
        └─ Hwloc.Object: Bridge [HostBridge]
          └─ Hwloc.Object: Bridge [PCIBridge]
            └─ Hwloc.Object: PCI_Device [81:00.0 (Ethernet)]
              └─ Hwloc.Object: OS_Device [Net "hsn1"]
        ...
      └─ Hwloc.Object: Group
        └─ Hwloc.Object: NUMANode
          └─ Hwloc.Object: Bridge [HostBridge]
            └─ Hwloc.Object: Bridge [PCIBridge]
              └─ Hwloc.Object: PCI_Device [42:00.0 (Ethernet)]
                └─ Hwloc.Object: OS_Device [Net "hsn2"]
          ...
        └─ Hwloc.Object: Group
          └─ Hwloc.Object: NUMANode
            └─ Hwloc.Object: Bridge [HostBridge]
              └─ Hwloc.Object: Bridge [PCIBridge]
                └─ Hwloc.Object: PCI_Device [01:00.0 (Ethernet)]
                  └─ Hwloc.Object: OS_Device [Net "hsn3"]
            ...
```

Eg. GPU Node Topology



```

Machine
├── Hwloc.Object: Package [L#0 P#0]
│   ├── Hwloc.Object: Group
│   │   ├── Hwloc.Object: NUMANode
│   │   │   ├── Hwloc.Object: Bridge [HostBridge]
│   │   │   │   ├── Hwloc.Object: Bridge [PCIBridge]
│   │   │   │   │   ├── Hwloc.Object: PCI_Device [c2:00.0 (Ethernet)]
│   │   │   │   │   │   └── Hwloc.Object: OS_Device [Net "hsn0"]
│   │   │   │   │   └── Hwloc.Object: Bridge [PCIBridge]
│   │   │   │   │       ├── Hwloc.Object: PCI_Device [c3:00.0 (Ethernet)]
│   │   │   │   │       └── Hwloc.Object: OS_Device [Net "hmn0"]
│   │   │   └── ...
│   │   ├── Hwloc.Object: Group
│   │   │   ├── Hwloc.Object: NUMANode
│   │   │   │   ├── Hwloc.Object: Bridge [HostBridge]
│   │   │   │   │   ├── Hwloc.Object: Bridge [PCIBridge]
│   │   │   │   │   │   ├── Hwloc.Object: PCI_Device [81:00.0 (Ethernet)]
│   │   │   │   │   │   └── Hwloc.Object: OS_Device [Net "hsn1"]
│   │   │   │   └── ...
│   │   ├── Hwloc.Object: Group
│   │   │   ├── Hwloc.Object: NUMANode
│   │   │   │   ├── Hwloc.Object: Bridge [HostBridge]
│   │   │   │   │   ├── Hwloc.Object: Bridge [PCIBridge]
│   │   │   │   │   │   ├── Hwloc.Object: PCI_Device [42:00.0 (Ethernet)]
│   │   │   │   │   │   └── Hwloc.Object: OS_Device [Net "hsn2"]
│   │   │   │   └── ...
│   │   └── Hwloc.Object: Group
│   │       ├── Hwloc.Object: NUMANode
│   │       │   ├── Hwloc.Object: Bridge [HostBridge]
│   │       │   │   ├── Hwloc.Object: Bridge [PCIBridge]
│   │       │   │   │   ├── Hwloc.Object: PCI_Device [01:00.0 (Ethernet)]
│   │       │   │   │   └── Hwloc.Object: OS_Device [Net "hsn3"]
│   │       │   └── ...
│   └── ...

```

Topo distance to NIC

- Finding the right NIC is easy now: pick the (non-nmn) interface with lowest tree distance between your core and the PCI device



```
for net in collect(network_devs)
    found, dist = distance_to_core(hwloc_tree, net, cpu_id)
    print("${dist}: ")
    print_tree(net)
end
```

```
213: Hwloc.Object: PCI_Device [c2:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn0"]
213: Hwloc.Object: PCI_Device [c3:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "nmn0"]
47: Hwloc.Object: PCI_Device [81:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn1"]
379: Hwloc.Object: PCI_Device [42:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn2"]
379: Hwloc.Object: PCI_Device [01:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn3"]
```


Topo distance to NIC

- Finding the right NIC is easy now: pick the (non-nmn) interface with lowest tree distance between your core and the PCI device

This one! 

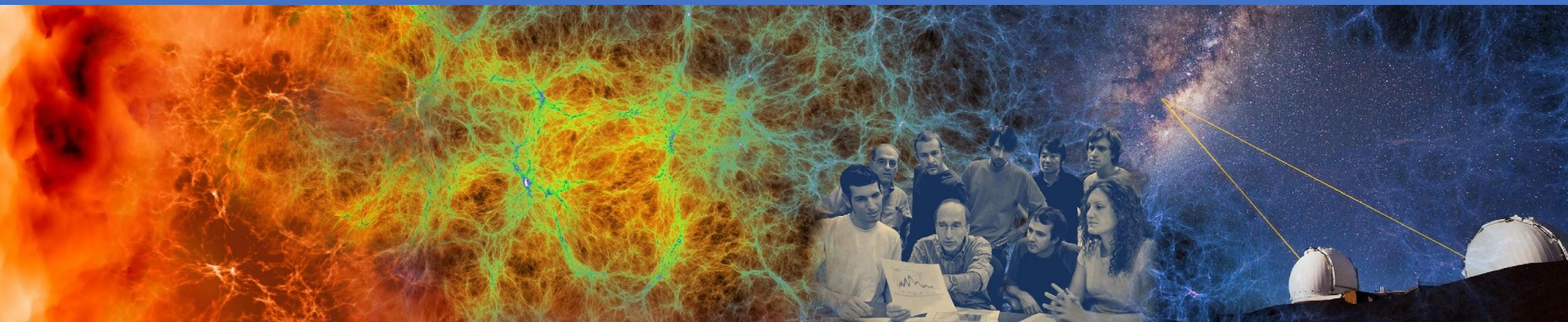
```
for net in collect(network_devs)
  found, dist = distance_to_core(hwloc_tree, net, cpu_id)
  print("${dist}: ")
  print_tree(net)
end
```

```
213: Hwloc.Object: PCI_Device [c2:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn0"]
213: Hwloc.Object: PCI_Device [c3:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "nmn0"]
47: Hwloc.Object: PCI_Device [81:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn1"]
379: Hwloc.Object: PCI_Device [42:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn2"]
379: Hwloc.Object: PCI_Device [01:00.0 (Ethernet)]
└─ Hwloc.Object: OS_Device [Net "hsn3"]
```

Future

- This is pre-alpha, so far only deployed at NERSC
 - Looking for folks to test this at NERSC and on their favorite HPC systems
- `Distributed.jl` to use distance between NIC and Core (on Hwloc tree) to select preferred tree NIC
 - [JuliaParallel/NetworkInterfaceControllers.jl](#)

Programming GPUs



CUDA.jl: Interfacing with Nvidia GPUs

SC23.ipynb (auto-L) - JupyterLab

File Edit View Run Kernel Git Tabs Settings Help

Code git SC23 Julia 1.9.3

```
[9]: arr1 = rand(1_000, 1_000);  
arr2 = rand(1_000, 1_000);
```

```
[10]: @benchmark arr1 * arr2
```

```
[10]: BenchmarkTools.Trial: 1493 samples with 1 evaluation.  
Range (min ... max): 2.626 ms ... 7.337 ms | GC (min ... max): 0.00% ... 2.79%  
Time (median): 3.152 ms | GC (median): 0.00%  
Time (mean ± σ): 3.347 ms ± 490.147 μs | GC (mean ± σ): 0.90% ± 1.83%
```

2.63 ms Histogram: frequency by time 4.16 ms <

Memory estimate: 7.63 MiB, allocs estimate: 2.

```
[11]: using CUDA
```

```
[12]: carr1 = cu(arr1);  
carr2 = cu(arr2);
```

```
[13]: @benchmark carr1 * carr2
```

```
[13]: BenchmarkTools.Trial: 10000 samples with 1 evaluation.  
Range (min ... max): 22.533 μs ... 390.183 μs | GC (min ... max): 0.00% ... 0.00%  
Time (median): 121.205 μs | GC (median): 0.00%  
Time (mean ± σ): 114.948 μs ± 24.119 μs | GC (mean ± σ): 0.00% ± 0.00%
```

22.5 μs Histogram: log(frequency) by time 123 μs <

Memory estimate: 1.09 KiB, allocs estimate: 44.

CUDA.jl: Interfacing with Nvidia GPUs

Basic example:
1000x1000 matmul
using OpenBLAS

```
[9]: arr1 = rand(1_000, 1_000);  
arr2 = rand(1_000, 1_000);
```

```
[10]: @benchmark arr1 * arr2
```

```
10]: BenchmarkTools.Trial: 1493 samples with 1 evaluation.  
Range (min ... max): 2.626 ms ... 7.337 ms | GC (min ... max): 0.00% ... 2.79%  
Time (median): 3.152 ms | GC (median): 0.00%  
Time (mean ± σ): 3.347 ms ± 490.147 μs | GC (mean ± σ): 0.90% ± 1.83%
```

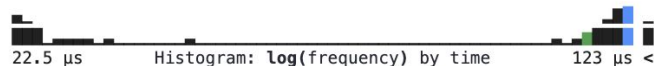


Memory estimate: 7.63 MiB, allocs estimate: 2.

```
[12]: carr1 = cu(arr1);  
carr2 = cu(arr2);
```

```
[13]: @benchmark carr1 * carr2
```

```
[13]: BenchmarkTools.Trial: 10000 samples with 1 evaluation.  
Range (min ... max): 22.533 μs ... 390.183 μs | GC (min ... max): 0.00% ... 0.00%  
Time (median): 121.205 μs | GC (median): 0.00%  
Time (mean ± σ): 114.948 μs ± 24.119 μs | GC (mean ± σ): 0.00% ± 0.00%
```



Memory estimate: 1.09 KiB, allocs estimate: 44.

CUDA.jl: Interfacing with Nvidia GPUs

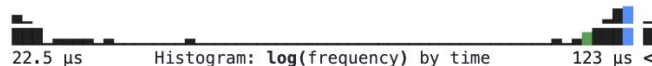
```
SC23.ipynb (auto-L) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
Code git SC23 Julia 1.9.3
[9]: arr1 = rand(1_000, 1_000);
    arr2 = rand(1_000, 1_000);
[10]: @benchmark arr1 * arr2
[10]: BenchmarkTools.Trial: 1493 samples with 1 evaluation.
      Range (min ... max):  2.626 ms ...  7.337 ms  GC (min ... max): 0.00% ... 2.79%
      Time (median):       3.152 ms              GC (median):  0.00%
      Time (mean ± σ):     3.347 ms ± 490.147 μs  GC (mean ± σ): 0.90% ± 1.83%
Histogram: frequency by time
2.63 ms 4.16 ms <
```

Copy arrays to device

```
[11]: using CUDA
```

```
[12]: carr1 = cu(arr1);
      carr2 = cu(arr2);
```

```
[13]: BenchmarkTools.Trial: 10000 samples with 1 evaluation.
      Range (min ... max):  22.533 μs ... 390.183 μs  GC (min ... max): 0.00% ... 0.00%
      Time (median):       121.205 μs              GC (median):  0.00%
      Time (mean ± σ):     114.948 μs ± 24.119 μs    GC (mean ± σ): 0.00% ± 0.00%
```



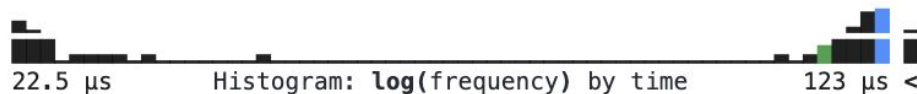
Memory estimate: 1.09 KiB, allocs estimate: 44.

CUDA.jl 1: Interfacing with Nvidia GPUs

```
SC23.ipynb (auto-L) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
Code git SC23 Julia 1.9.3
[9]: arr1 = rand(1_000, 1_000);
    arr2 = rand(1_000, 1_000);
[10]: @benchmark arr1 * arr2
[10]: BenchmarkTools.Trial: 1493 samples with 1 evaluation.
      Range (min ... max):  2.626 ms ...  7.337 ms  | GC (min ... max): 0.00% ... 2.79%
      Time (median):       3.152 ms                | GC (median): 0.00%
      Time (mean ± σ):     3.347 ms ± 490.147 μs    | GC (mean ± σ): 0.90% ± 1.83%
      Histogram: frequency by time
      2.63 ms 4.16 ms <
      Memory estimate: 7.63 MiB, allocs estimate: 2.
```

```
[13]: @benchmark carr1 * carr2
```

```
[13]: BenchmarkTools.Trial: 10000 samples with 1 evaluation.
      Range (min ... max):  22.533 μs ... 390.183 μs | GC (min ... max): 0.00% ... 0.00%
      Time (median):       121.205 μs                | GC (median): 0.00%
      Time (mean ± σ):     114.948 μs ± 24.119 μs    | GC (mean ± σ): 0.00% ± 0.00%
```

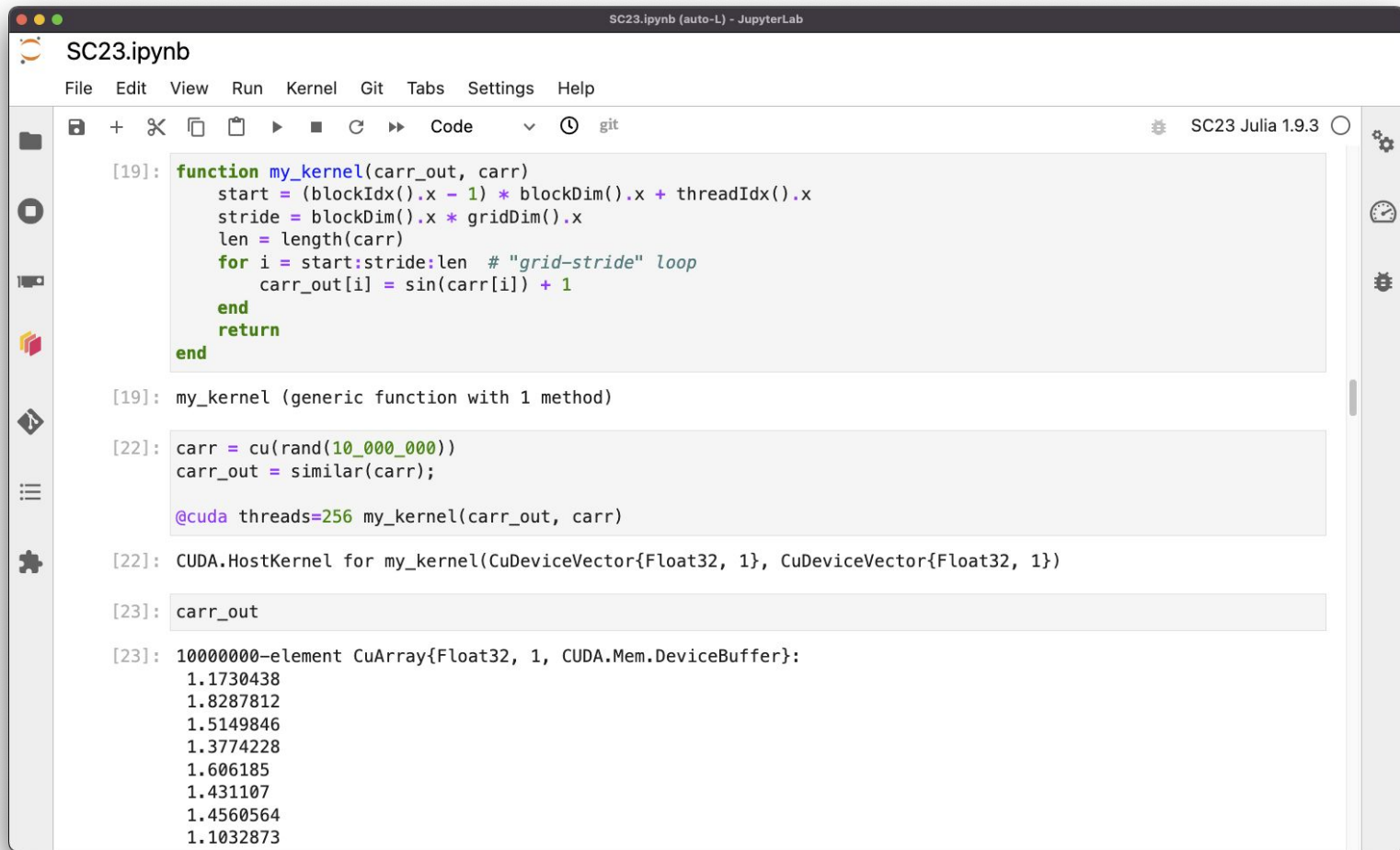


```
Memory estimate: 1.09 KiB, allocs estimate: 44.
```

Using cuBLAS to perform matmul decreases run time from 3.15ms to 121μs (26x)



Write Your Own CUDA Kernels in Julia



The screenshot shows a JupyterLab notebook titled "SC23.ipynb" with the following content:

```
[19]: function my_kernel(carr_out, carr)
      start = (blockIdx().x - 1) * blockDim().x + threadIdx().x
      stride = blockDim().x * gridDim().x
      len = length(carr)
      for i = start:stride:len # "grid-stride" loop
          carr_out[i] = sin(carr[i]) + 1
      end
      return
  end
```

[19]: my_kernel (generic function with 1 method)

```
[22]: carr = cu(rand(10_000_000))
      carr_out = similar(carr);

      @cuda threads=256 my_kernel(carr_out, carr)
```

[22]: CUDA.HostKernel for my_kernel(CuDeviceVector{Float32, 1}, CuDeviceVector{Float32, 1})

```
[23]: carr_out
```

[23]: 10000000-element CuArray{Float32, 1, CUDA.Mem.DeviceBuffer}:
1.1730438
1.8287812
1.5149846
1.3774228
1.606185
1.431107
1.4560564
1.1032873

Write Your Own CUDA Kernels in Julia

Define kernels using
Julia functions

```
[19]: function my_kernel(carr_out, carr)
      start = (blockIdx().x - 1) * blockDim().x + threadIdx().x
      stride = blockDim().x * gridDim().x
      len = length(carr)
      for i = start:stride:len # "grid-stride" loop
          carr_out[i] = sin(carr[i]) + 1
      end
      return
  end
```

```
[22]: carr = cu(rand(10_000_000))
      carr_out = similar(carr);

      @cuda threads=256 my_kernel(carr_out, carr)
```

```
[22]: CUDA.HostKernel for my_kernel(CuDeviceVector{Float32, 1}, CuDeviceVector{Float32, 1})
```

```
[23]: carr_out
```

```
[23]: 10000000-element CuArray{Float32, 1, CUDA.Mem.DeviceBuffer}:
      1.1730438
      1.8287812
      1.5149846
      1.3774228
      1.606185
      1.431107
      1.4560564
      1.1032873
```

Write Your Own CUDA Kernels in Julia

```
SC23.ipynb (auto-L) - JupyterLab
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[19]: function my_kernel(carr_out, carr)
      start = (blockIdx().x - 1) * blockDim().x + threadIdx().x
      stride = blockDim().x * gridDim().x
      len = length(carr)
      for i = start:stride:len # "grid-stride" loop
          carr_out[i] = sin(carr[i]) + 1
      end
      return
  end
end

[19]: my_kernel (generic function with 1 method)
```

Launch kernel using the
`@cuda` macro

```
[22]: carr = cu(rand(10_000_000))
      carr_out = similar(carr);
      @cuda threads=256 my_kernel(carr_out, carr)
```

```
[22]: CUDA.HostKernel for my_kernel(CuDeviceVector{Float32, 1}, CuDeviceVector{Float32, 1})
```

```
[23]: 10000000-element CuArray{Float32, 1, CUDA.Mem.DeviceBuffer}:
      1.1730438
      1.8287812
      1.5149846
      1.3774228
      1.606185
      1.431107
      1.4560564
      1.1032873
```



CUDA.jl provides detailed profiling interface

SC23.ipynb (auto-L) - JupyterLab

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```
[14]: CUDA.@profile carr1 * carr2
```

[14]: Profiler ran for 2.23 ms, capturing 23 events.

Host-side activity: calling CUDA APIs took 1.96 ms (87.81% of the trace)

Time (%)	Time	Calls	Avg time	Min time	Max time	Name	...
29.29%	653.51 μ s	1	653.51 μ s	653.51 μ s	653.51 μ s	cuMemAllo ...	
18.15%	404.83 μ s	1	404.83 μ s	404.83 μ s	404.83 μ s	cudaEvent ...	
1.12%	25.03 μ s	1	25.03 μ s	25.03 μ s	25.03 μ s	cudaLaunc ...	
0.82%	18.36 μ s	1	18.36 μ s	18.36 μ s	18.36 μ s	cudaMemse ...	
0.44%	9.78 μ s	2	4.89 μ s	953.67 ns	8.82 μ s	cudaOccup ...	
0.28%	6.2 μ s	3	2.07 μ s	476.84 ns	4.77 μ s	cudaStrea ...	
0.26%	5.72 μ s	1	5.72 μ s	5.72 μ s	5.72 μ s	cudaEvent ...	
0.00%	0.0 ns	1	0.0 ns	0.0 ns	0.0 ns	cudaGetLa ...	

1 column omitted

Device-side activity: GPU was busy for 160.22 μ s (7.18% of the trace)

Time (%)	Time	Calls	Avg time	Min time	Max time	Name	...
7.09%	158.07 μ s	1	158.07 μ s	158.07 μ s	158.07 μ s	ampere_sg ...	
0.10%	2.15 μ s	1	2.15 μ s	2.15 μ s	2.15 μ s	[set devi ...	

1 column omitted

(advanced) LLVM + Julia

Julia provides
interfaces to the
LLVM backend.

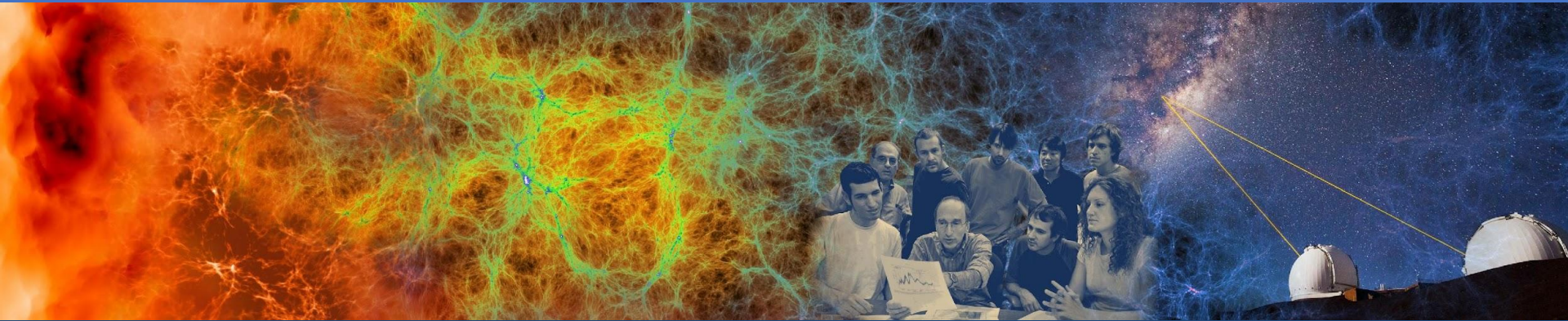
Eg.:

- `loopinfo`
- `llvmcall`

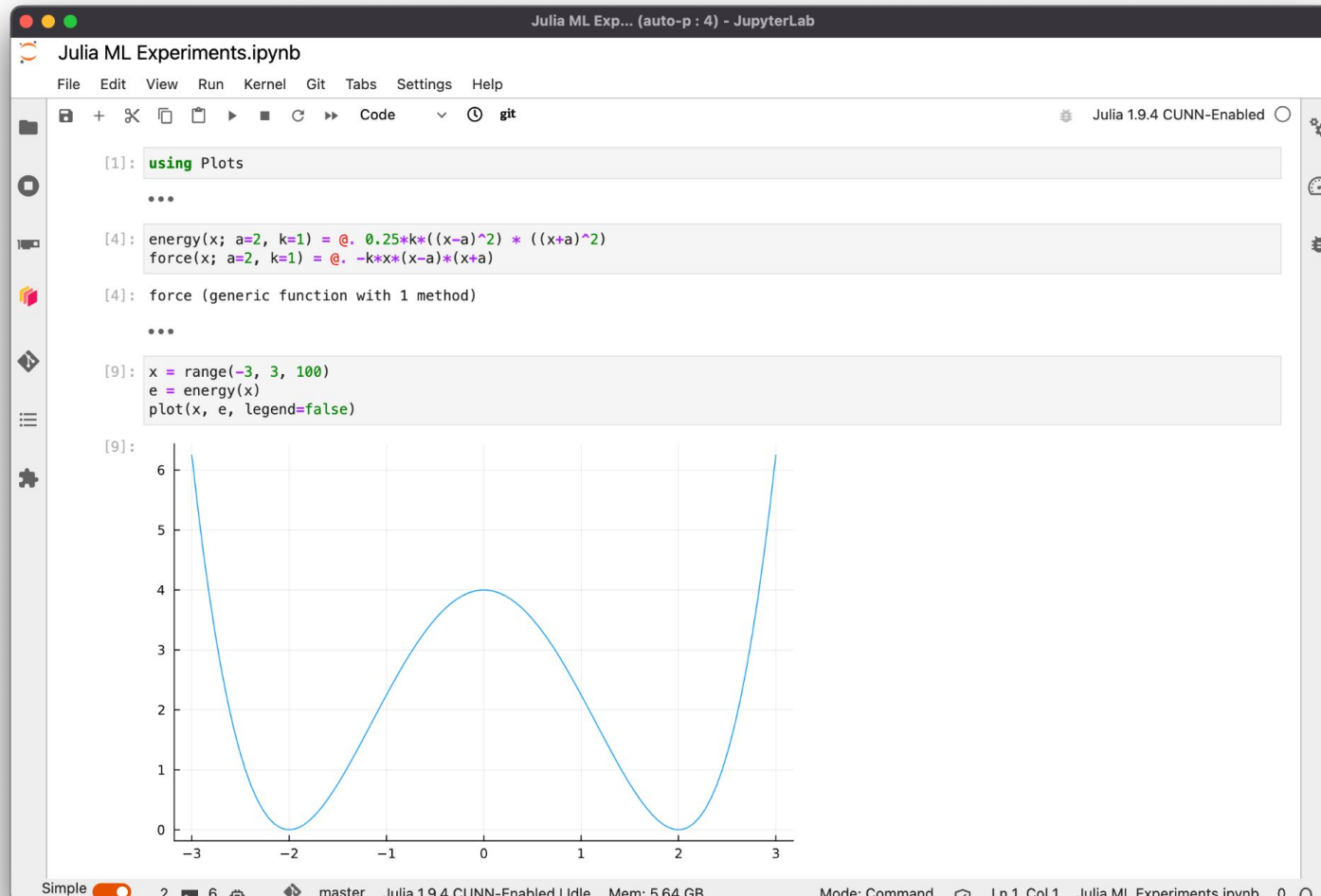
```
[16]: macro unroll(expr)
    expr = loopinfo("@unroll", expr, (Symbol("llvm.loop.unroll.full"),))
    return esc(expr)
end

for (jlf, f) in zip((:+, :*, :-), (:add, :mul, :sub))
    for (T, llvmT) in (:(Float32, "float"), :(Float64, "double"))
        ir = ""
        %x = f$f contract nsz $llvmT %0, %1
        ret $llvmT %x
        ""
        @eval begin
            # the @pure is necessary so that we can constant propagate.
            @inline Base.@pure function jlf(a::$T, b::$T)
                Base.llvmcall($ir, $T, Tuple{$T, $T}, a, b)
            end
        end
    end
end
@eval function jlf(args...)
    Base.$jlf(args...)
end
end
```

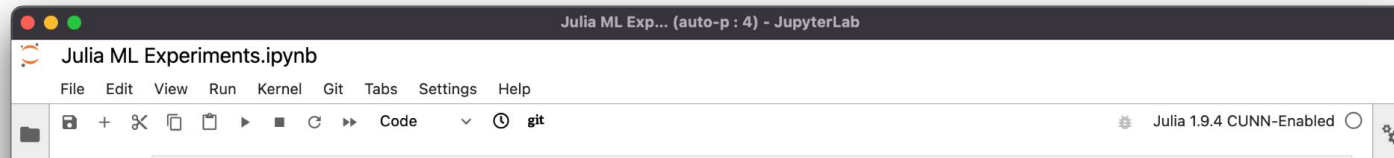
Inspiration: Particles in Potentials



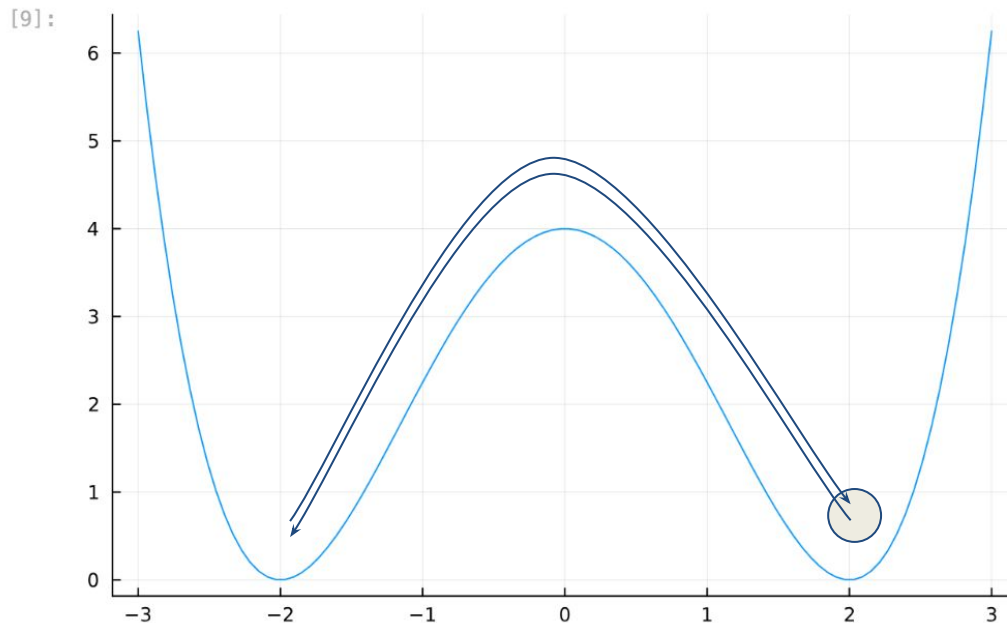
Transition Rates between Potential Minima



Transition Rates between Potential Minima

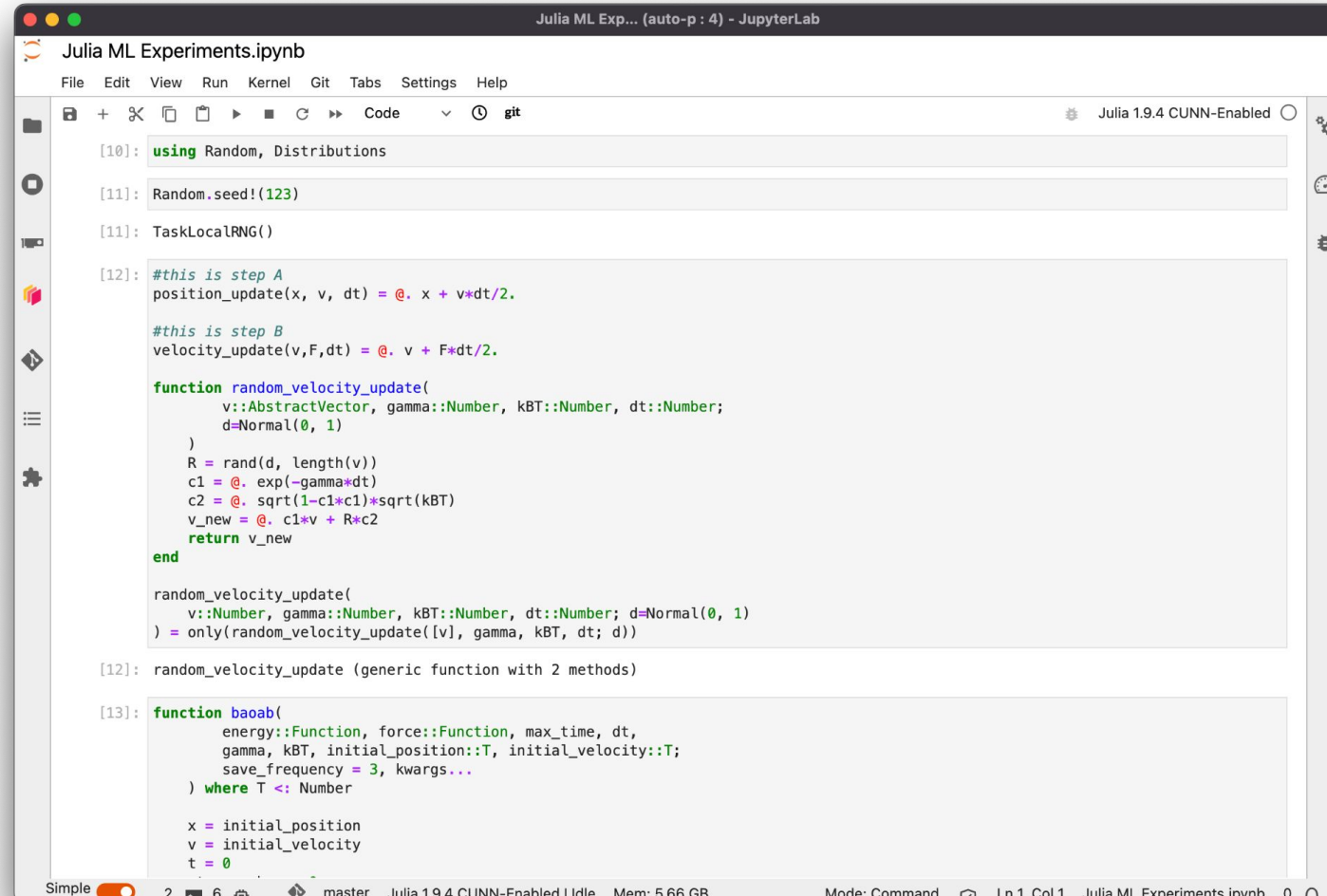


```
[9]: x = range(-3, 3, 100)
     e = energy(x)
     plot(x, e, legend=false)
```



This is a highly-simplified (1D) model for loads of interesting science: chemical reactions; protein conformations; etc

Integrating SDEs



```
Julia ML Exp... (auto-p : 4) - JupyterLab
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[10]: using Random, Distributions

[11]: Random.seed!(123)

[11]: TaskLocalRNG()

[12]: #this is step A
      position_update(x, v, dt) = @. x + v*dt/2.

      #this is step B
      velocity_update(v,F,dt) = @. v + F*dt/2.

      function random_velocity_update(
          v::AbstractVector, gamma::Number, kBT::Number, dt::Number;
          d=Normal(0, 1)
      )
          R = rand(d, length(v))
          c1 = @. exp(-gamma*dt)
          c2 = @. sqrt(1-c1*c1)*sqrt(kBT)
          v_new = @. c1*v + R*c2
          return v_new
      end

      random_velocity_update(
          v::Number, gamma::Number, kBT::Number, dt::Number; d=Normal(0, 1)
      ) = only(random_velocity_update([v], gamma, kBT, dt; d))

[12]: random_velocity_update (generic function with 2 methods)

[13]: function baoab(
          energy::Function, force::Function, max_time, dt,
          gamma, kBT, initial_position::T, initial_velocity::T;
          save_frequency = 3, kwargs...
      ) where T <: Number

          x = initial_position
          v = initial_velocity
          t = 0
```



Integrating SDEs

Julia makes RNG easy!

```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
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[10]: using Random, Distributions

[11]: Random.seed!(123)

[11]: TaskLocalRNG()

#this is step B
velocity_update(v,F,dt) = @. v + F*dt/2.

function random_velocity_update(
    v::AbstractVector, gamma::Number, kBT::Number, dt::Number;
    d=Normal(0, 1)
)
    R = rand(d, length(v))
    c1 = @. exp(-gamma*dt)
    c2 = @. sqrt(1-c1*c1)*sqrt(kBT)
    v_new = @. c1*v + R*c2
    return v_new
end

random_velocity_update(
    v::Number, gamma::Number, kBT::Number, dt::Number; d=Normal(0, 1)
) = only(random_velocity_update([v], gamma, kBT, dt; d))

[12]: random_velocity_update (generic function with 2 methods)

[13]: function baoab(
    energy::Function, force::Function, max_time, dt,
    gamma, kBT, initial_position::T, initial_velocity::T;
    save_frequency = 3, kwargs...
) where T <: Number

    x = initial_position
    v = initial_velocity
    t = 0
```



Integrating SDEs

```
Julia ML Exp... (auto-p: 4) - JupyterLab
Julia ML Experiments.ipynb
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[10]: using Random, Distributions
[11]: Random.seed!(123)
[11]: TaskLocalRNG()
[12]: #this is step A
```

```
[12]: #this is step A
position_update(x, v, dt) = @. x + v*dt/2.

#this is step B
velocity_update(v,F,dt) = @. v + F*dt/2.

function random_velocity_update(
    v::AbstractVector, gamma::Number, kBT::Number, dt::Number;
    d=Normal(0, 1)
)
    R = rand(d, length(v))
    c1 = @. exp(-gamma*dt)
    c2 = @. sqrt(1-c1*c1)*sqrt(kBT)
    v_new = @. c1*v + R*c2
    return v_new
end

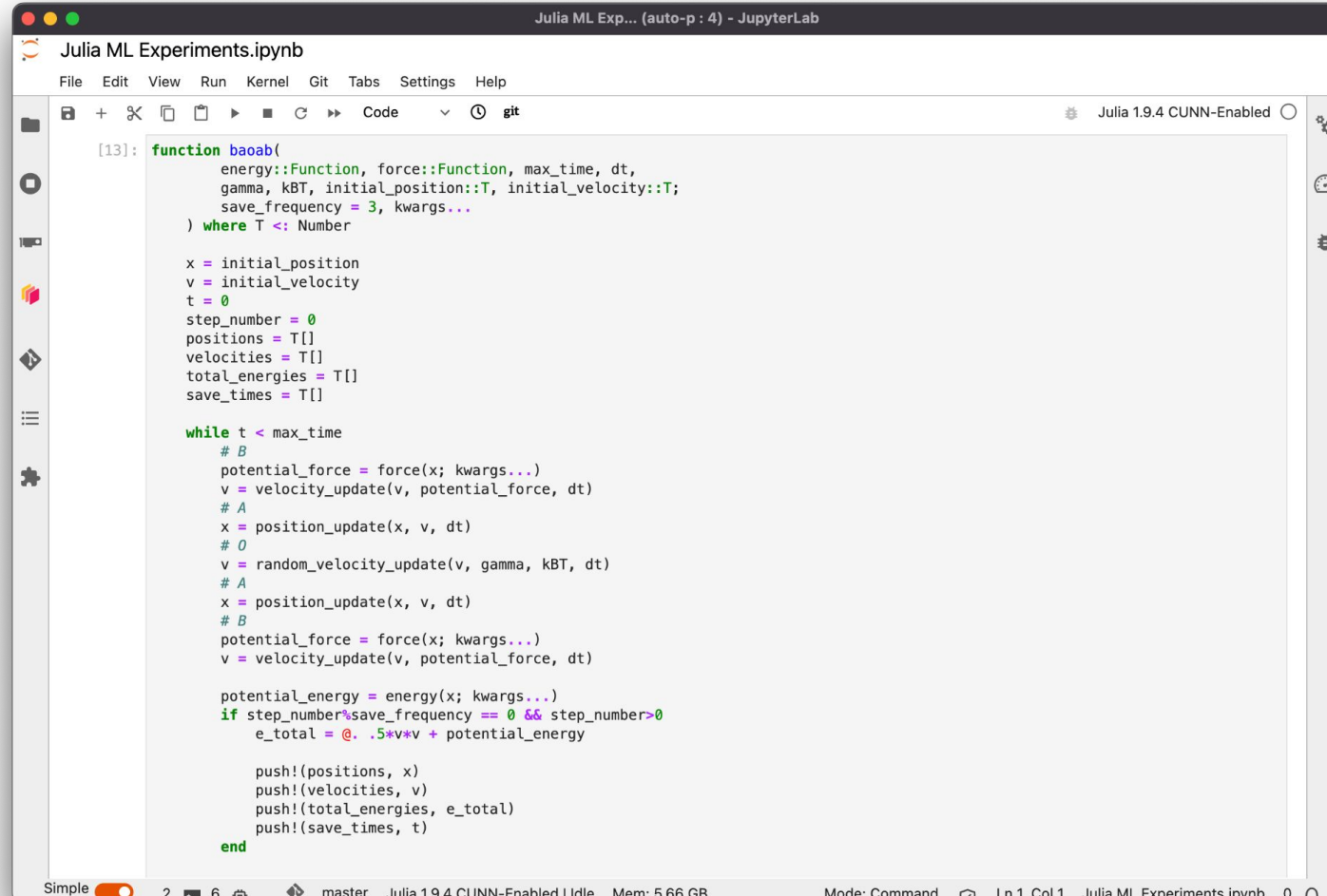
random_velocity_update(
    v::Number, gamma::Number, kBT::Number, dt::Number; d=Normal(0, 1)
) = only(random_velocity_update([v], gamma, kBT, dt; d))
```

Define SDE algorithm



Integrating SDEs

SDE algorithms can be long and complex!



```
Julia ML Exp... (auto-p : 4) - JupyterLab
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[13]: function baobab(
    energy::Function, force::Function, max_time, dt,
    gamma, kBT, initial_position::T, initial_velocity::T;
    save_frequency = 3, kwargs...
) where T <: Number

    x = initial_position
    v = initial_velocity
    t = 0
    step_number = 0
    positions = T[]
    velocities = T[]
    total_energies = T[]
    save_times = T[]

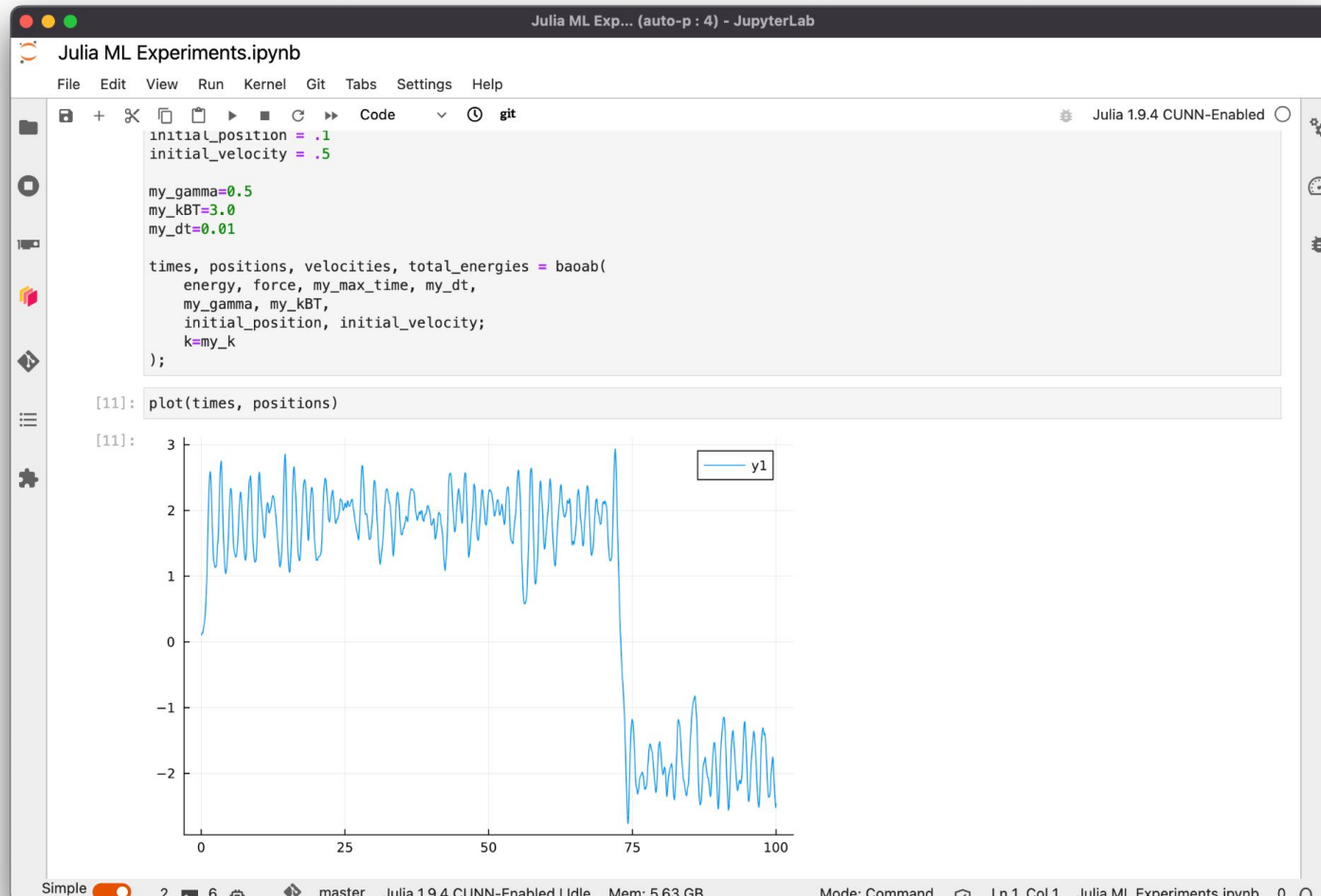
    while t < max_time
        # B
        potential_force = force(x; kwargs...)
        v = velocity_update(v, potential_force, dt)
        # A
        x = position_update(x, v, dt)
        # O
        v = random_velocity_update(v, gamma, kBT, dt)
        # A
        x = position_update(x, v, dt)
        # B
        potential_force = force(x; kwargs...)
        v = velocity_update(v, potential_force, dt)

        potential_energy = energy(x; kwargs...)
        if step_number%save_frequency == 0 && step_number>0
            e_total = @. .5*v*v + potential_energy

            push!(positions, x)
            push!(velocities, v)
            push!(total_energies, e_total)
            push!(save_times, t)
        end
    end
end
```

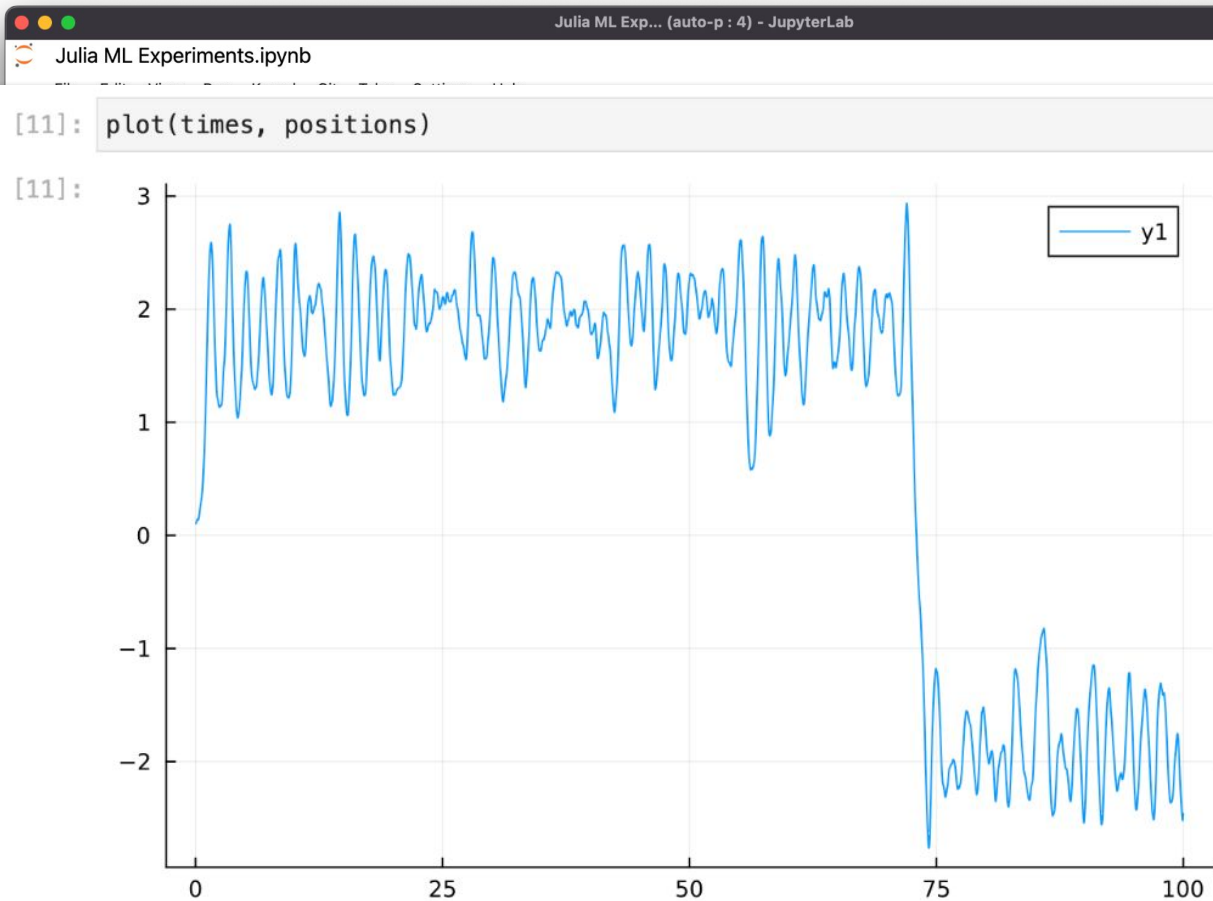


Transitions are Rare!



Transitions are Rare!

Often you will 100s of millions of data points in order to collect a few thousand transitions



Solution Strategy: Local Monte-Carlo Sampling

```
Julia ML Exp... (auto-p: 4) - JupyterLab
Julia ML Experiments.ipynb
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Code git Julia 1.9.4 CUNN-Enabled

[13]: function baoab_ensemble(
    energy::Function, force::Function, max_time, dt,
    gamma, kBT, initial_position::T, initial_velocity::T;
    save_frequency = 3, ensemble = (len=10, d=Normal(0, 0.01), n=10, st=10),
    kwargs...
) where T <: Number

    times, positions, velocities, total_energies = baoab(
        energy, force, max_time, dt,
        gamma, kBT, initial_position, initial_velocity;
        save_frequency=save_frequency, kwargs...
    )

    ensemble_t = Array{T, 1}[]
    ensemble_p = Array{T, 1}[]
    ensemble_v = Array{T, 1}[]
    for (t, p, v) in zip(
        times[1:ensemble.st:end],
        positions[1:ensemble.st:end],
        velocities[1:ensemble.st:end]
    )
        p_r = rand(ensemble.d, ensemble.n)
        v_r = rand(ensemble.d, ensemble.n)

        for i in 1:ensemble.n
            t_i, p_i, v_i, _ = baoab(
                energy, force, ensemble.len*dt, dt,
                gamma, kBT, p + p_r[i], v + v_r[i];
                save_frequency=save_frequency, kwargs...
            )
            push!(ensemble_t, t + t_i)
            push!(ensemble_p, p_i)
            push!(ensemble_v, v_i)
        end
    end
end

return times, positions, velocities, total_energies, (t=ensemble_t, p=ensemble_p, v=ensemble_v)
end
```



Solution Strategy: Local Monte-Carlo Sampling

```
Julia ML Exp... (auto-n: 4) - JupyterLab  
times, positions, velocities, total_energies = baoab(  
    energy, force, max_time, dt,  
    gamma, kBT, initial_position, initial_velocity;  
    save_frequency=save_frequency, kwargs...  
)  
  
ensemble_t = Array{T, 1}[]  
ensemble_p = Array{T, 1}[]  
ensemble_v = Array{T, 1}[]  
for (t, p, v) in zip(  
    times[1:ensemble.st:end],  
    positions[1:ensemble.st:end],  
    velocities[1:ensemble.st:end]  
)  
    p_r = rand(ensemble.d, ensemble.n)  
    v_r = rand(ensemble.d, ensemble.n)  
  
    for i in 1:ensemble.n  
        t_i, p_i, v_i, _ = baoab(  
            energy, force, ensemble.len*dt, dt,  
            gamma, kBT, p + p_r[i], v + v_r[i];  
            save_frequency=save_frequency, kwargs...  
        )  
        push!(ensemble_t, t .+ t_i)  
        push!(ensemble_p, p_i)  
        push!(ensemble_v, v_i)  
    end  
end
```

Solution Strategy: Local Monte-Carlo Sampling

For every time step, run a short simulation with slightly different starting conditions

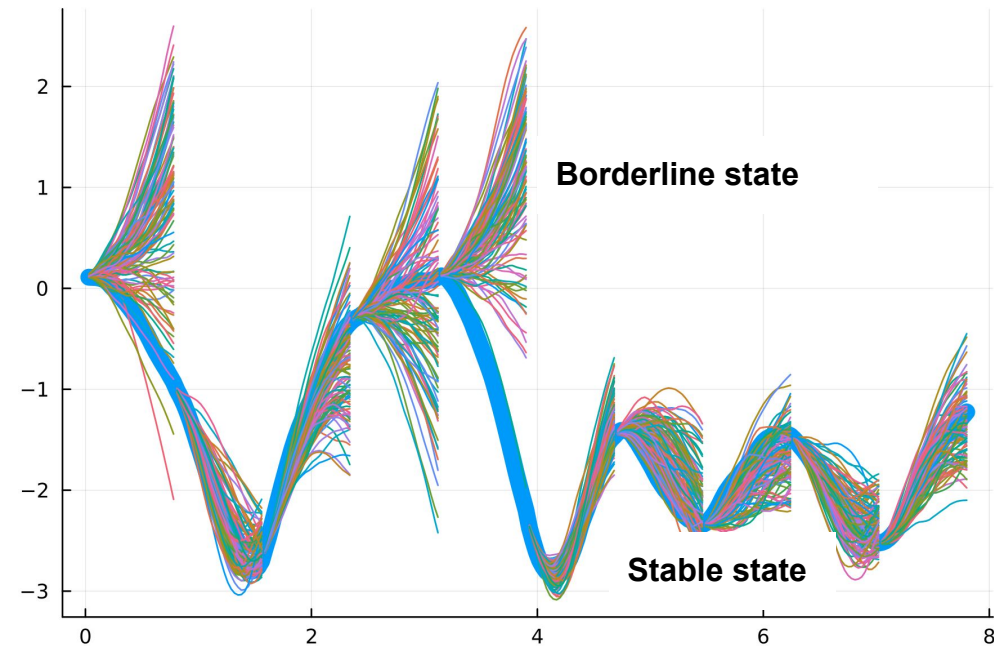
```
times, positions, velocities, total_energies = baoab(
    energy, force, max_time, dt,
    gamma, kBT, initial_position, initial_velocity;
    save_frequency=save_frequency, kwargs...
)

ensemble_t = Array{T, 1}[]
ensemble_p = Array{T, 1}[]
ensemble_v = Array{T, 1}[]
for (t, p, v) in zip(
    times[1:ensemble.st:end],
    positions[1:ensemble.st:end],
    velocities[1:ensemble.st:end]
)
    p_r = rand(ensemble.d, ensemble.n)
    v_r = rand(ensemble.d, ensemble.n)

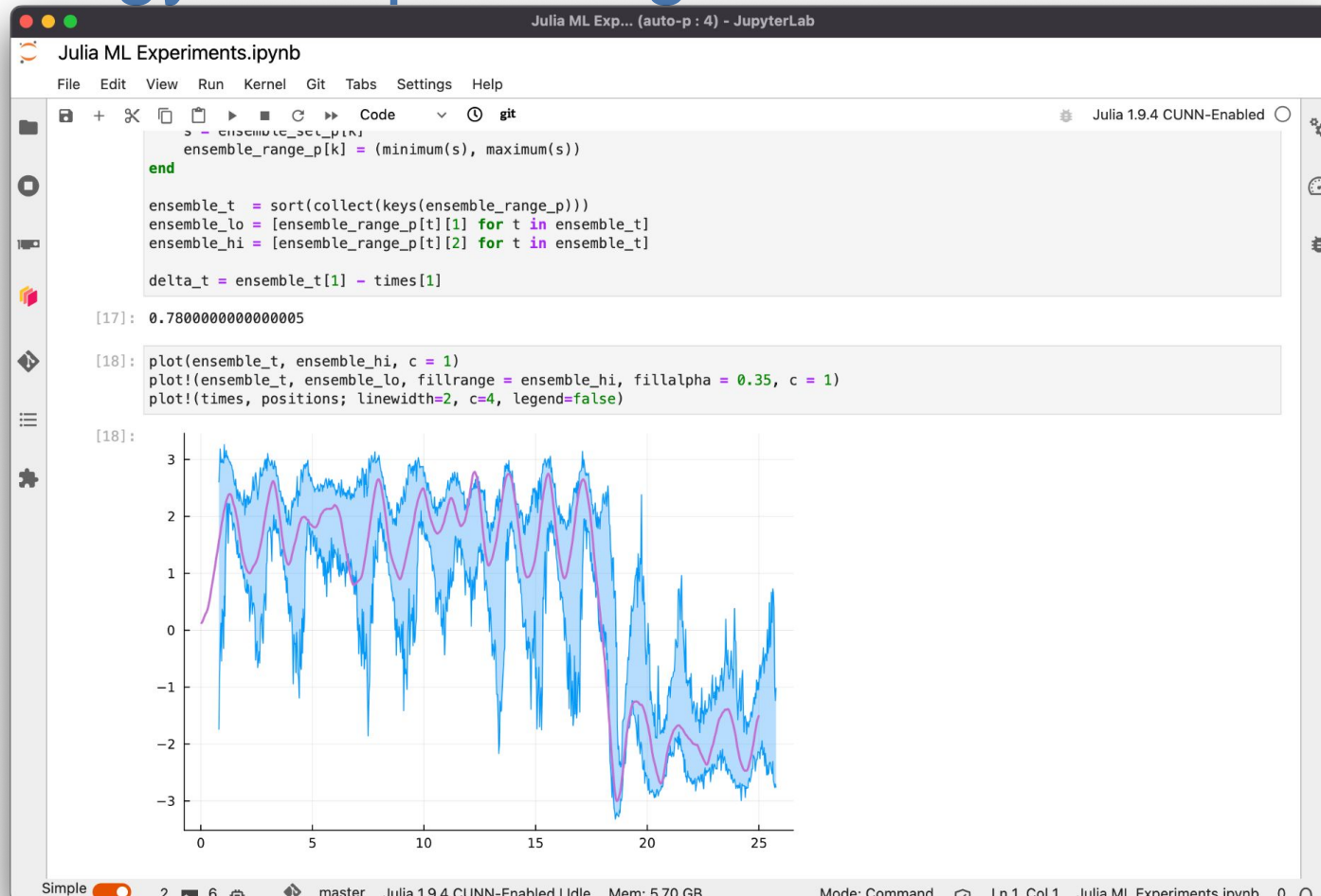
    for i in 1:ensemble.n
        t_i, p_i, v_i, _ = baoab(
            energy, force, ensemble.len*dt, dt,
            gamma, kBT, p + p_r[i], v + v_r[i];
            save_frequency=save_frequency, kwargs...
        )
        push!(ensemble_t, t .+ t_i)
        push!(ensemble_p, p_i)
        push!(ensemble_v, v_i)
    end
end
```


Solution Strategy: Local Monte-Carlo Sampling

```
times, positions, velocities, total_energies = baoab(  
    energy, force, max_time, dt,  
    gamma, kBT, initial_position, initial_velocity;  
    save_frequency=save_frequency, kwargs...  
)  
  
ensemble_t = Array{T, 1}[]  
ensemble_p = Array{T, 1}[]  
ensemble_v = Array{T, 1}[]  
for i in 1:ensemble.len  
    zip(  
        ensemble.st:end],  
        [1:ensemble.st:end],  
        s[1:ensemble.st:end])  
    semble.d, ensemble.n)  
    semble.d, ensemble.n)  
  
semble.n  
v_i, _ = baoab(  
y, force, ensemble.len*dt, dt,  
, kBT, p + p_r[i], v + v_r[i];  
frequency=save_frequency, kwargs...  
  
emblem_t, t .+ t_i)  
emblem_p, p_i)  
emblem_v, v_i)
```



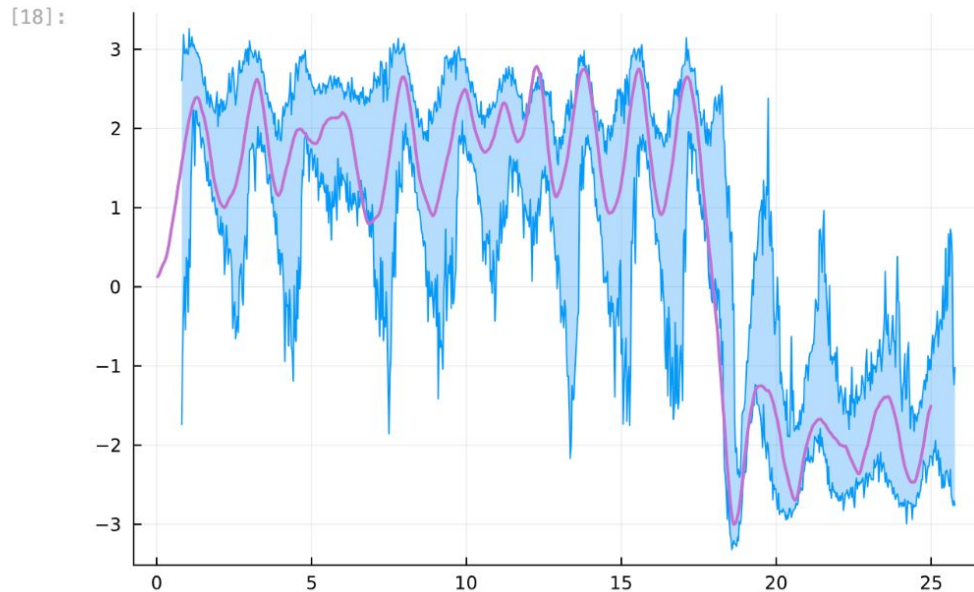
Solution Strategy: Adaptive Algorithms



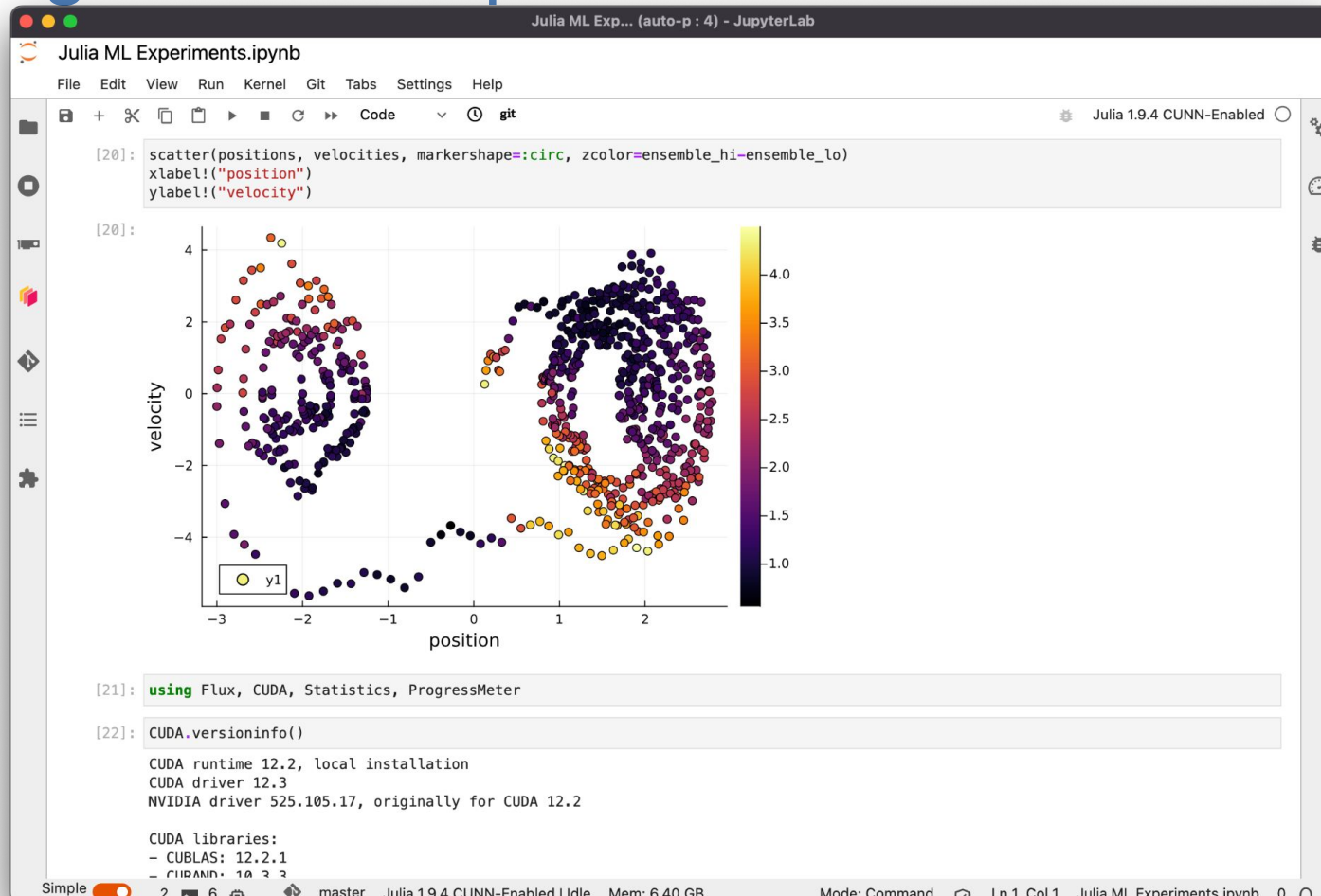
Solution Strategy: Adaptive Algorithms

```
Julia ML Exp... (auto-p: 4) - JupyterLab  
Julia ML Experiments.ipynb  
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s - ensemble_lo_p[k]  
ensemble_range_p[k] = (minimum(s), maximum(s))  
end
```

```
[18]: plot(ensemble_t, ensemble_hi, c = 1)  
plot!(ensemble_t, ensemble_lo, fillrange = ensemble_hi, fillalpha = 0.35, c = 1)  
plot!(times, positions; linewidth=2, c=4, legend=false)
```

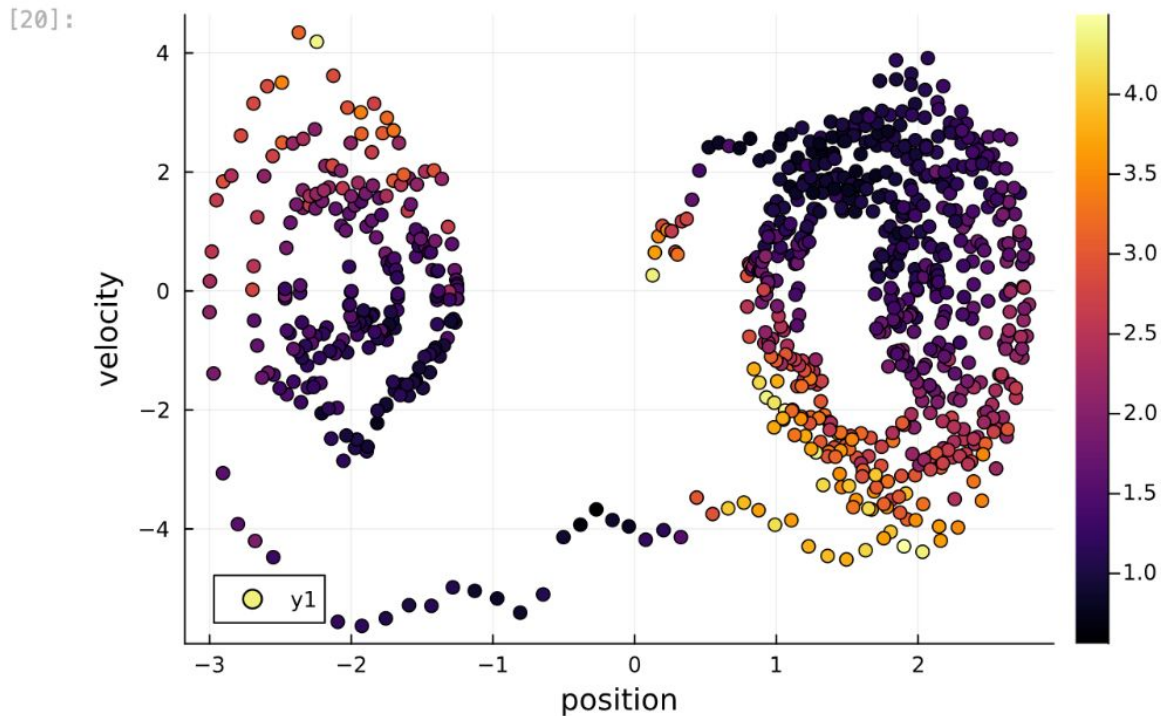


Start Mapping a Phase Space

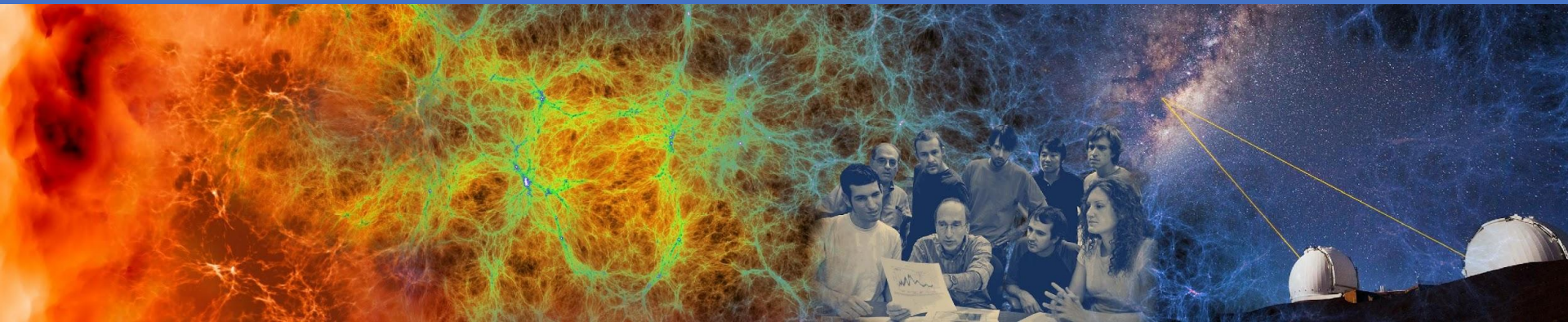


Start Mapping a Phase Space

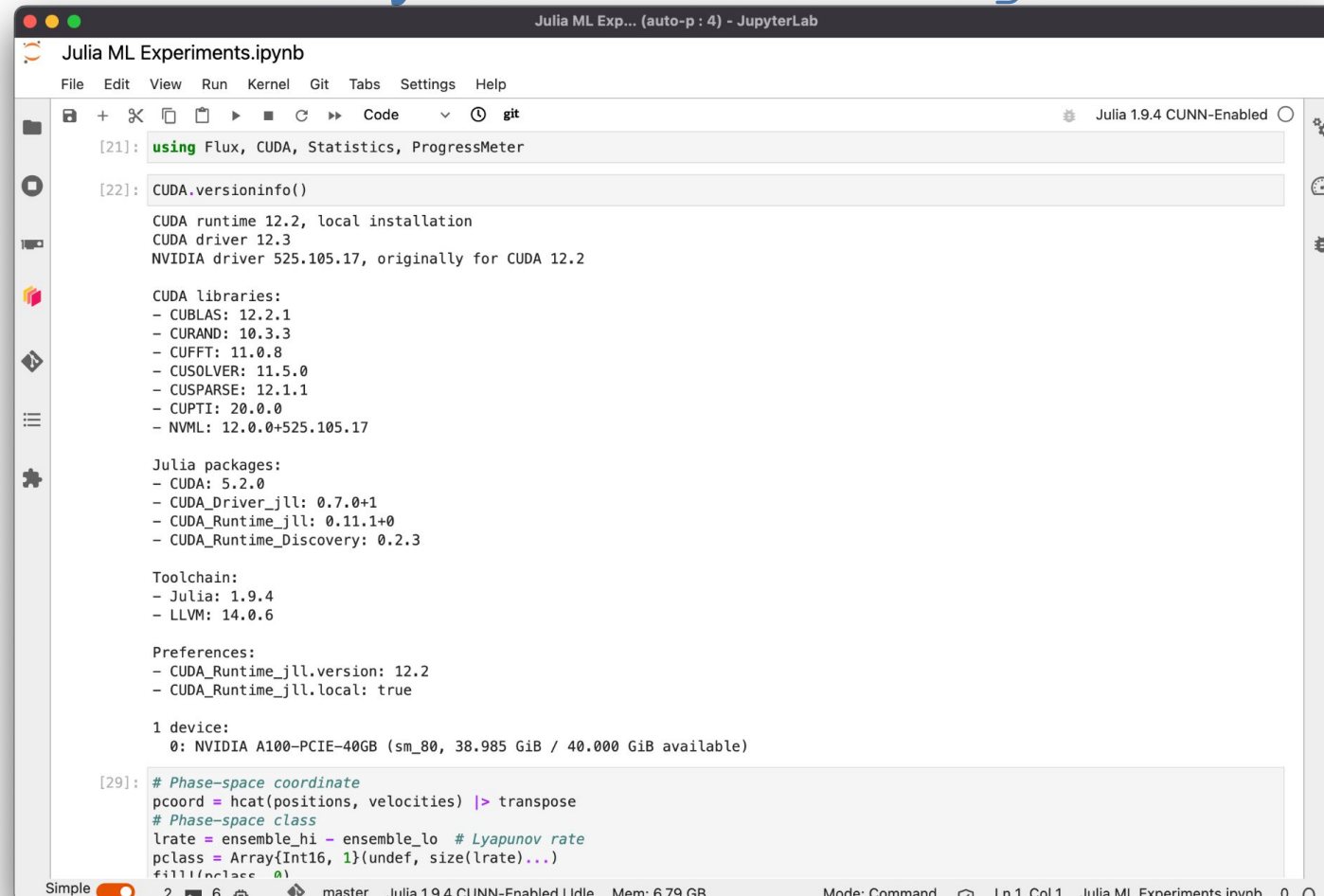
```
[20]: scatter(positions, velocities, markershape=:circ, zcolor=ensemble_hi-ensemble_lo)
      xlabel!("position")
      ylabel!("velocity")
```



Machine learning using Flux.jl



Flux.jl Automatically Detects CUDA.jl



The screenshot shows a JupyterLab window titled "Julia ML Experiments.ipynb" with the following content:

```
[21]: using Flux, CUDA, Statistics, ProgressMeter

[22]: CUDA.versioninfo()

CUDA runtime 12.2, local installation
CUDA driver 12.3
NVIDIA driver 525.105.17, originally for CUDA 12.2

CUDA libraries:
- CUBLAS: 12.2.1
- CURAND: 10.3.3
- CUFFT: 11.0.8
- CUSOLVER: 11.5.0
- CUSPARSE: 12.1.1
- CUPTI: 20.0.0
- NVML: 12.0.0+525.105.17

Julia packages:
- CUDA: 5.2.0
- CUDA_Driver_jll: 0.7.0+1
- CUDA_Runtime_jll: 0.11.1+0
- CUDA_Runtime_Discovery: 0.2.3

Toolchain:
- Julia: 1.9.4
- LLVM: 14.0.6

Preferences:
- CUDA_Runtime_jll.version: 12.2
- CUDA_Runtime_jll.local: true

1 device:
 0: NVIDIA A100-PCIE-40GB (sm_80, 38.985 GiB / 40.000 GiB available)

[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble_hi - ensemble_lo # Lyapunov rate
pclass = Array{Int16, 1}(undef, size(lrate)...)
fill!(pclass, 0)
```

At the bottom of the window, the status bar shows: "Simple", "2", "6", "master", "Julia 1.9.4 CUNN-Enabled Idle", "Mem: 6.79 GB", "Mode: Command", "Ln 1 Col 1", "Julia ML Experiments.ipynb", and "0".



Flux.jl Automatically Detects CUDA.jl

```
[21]: using Flux, CUDA, Statistics, ProgressMeter
```

```
[22]: CUDA.versioninfo()
```

```
  CUDA runtime 12.2, local installation
  CUDA driver 12.3
  NVIDIA driver 525.105.17, originally for CUDA 12.2
```

```
  CUDA libraries:
```

```
- CUBLAS: 12.2.1
- CURAND: 10.3.3
- CUFFT: 11.0.8
- CUSOLVER: 11.5.0
- CUSPARSE: 12.1.1
- CUPTI: 20.0.0
- NVML: 12.0.0+525.105.17
```

```
  Julia packages:
```

```
- CUDA: 5.2.0
- CUDA_Driver_jll: 0.7.0+1
- CUDA_Runtime_jll: 0.11.1+0
- CUDA_Runtime_Discovery: 0.2.3
```

```
  Toolchain:
```

```
- Julia: 1.9.4
- LLVM: 14.0.6
```

```
  Preferences:
```

```
- CUDA_Runtime_jll.version: 12.2
- CUDA_Runtime_jll.local: true
```

```
  1 device:
```

```
  0: NVIDIA A100-PCIE-40GB (sm_80, 38.985 GiB / 40.000 GiB available)
```

Julia introspection is a powerful tool to detect / confirm system configuration

At NERSC Julia is configured to automatically detect the system's CUDA runtime



Define Input Data

```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
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[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble_hi - ensemble_lo # Lyapunov rate
pclass = Array{Int16, 1}(undef, size(lrate)...)
fill!(pclass, 0)
pclass[lrate .> 2] .= 1
pclass[lrate .> 3] .= 2;

[30]: N_coord = 2
N_class = 3
N_neuron = 8

model = Chain(
  Dense(N_coord => N_neuron, tanh),
  BatchNorm(N_neuron),
  Dense(N_neuron => N_class),
  softmax
) |> gpu # move model to GPU, if available

[30]: Chain(
  Dense(2 => 8, tanh), # 24 parameters
  BatchNorm(8), # 16 parameters, plus 16
  Dense(8 => 3), # 27 parameters
  NNlib.softmax,
) # Total: 6 trainable arrays, 67 parameters,
# plus 2 non-trainable, 16 parameters, summarysize 1.266 KiB.

[31]: # The model encapsulates parameters, randomly initialised. Its initial output is:
out1 = model(pcoord |> gpu) |> cpu # 2xN Matrix{Float32}

[31]: 3x833 Matrix{Float32}:
 0.30174  0.292602  0.286916  0.283165  ...  0.401954  0.436592  0.44925
 0.291435  0.260622  0.244021  0.235257  ...  0.362114  0.384997  0.391649
 0.406825  0.446776  0.469063  0.481578  ...  0.235932  0.17841  0.159102

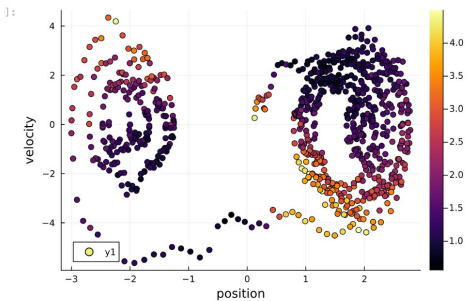
[32]: # To train the model, we use batches of 128 samples, and one-hot encoding:
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
loader = Flux.DataLoader((pcoord, target) |> gpu, batchsize=128, shuffle=true);
```



Define Input Data

Classify point in phase space based on local MC sample's spread rate (~Lyapunov rate)

```
[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble_hi - ensemble_lo # Lyapunov rate
pclass = Array{Int16, 1}(undef, size(lrate)...)
fill!(pclass, 0)
pclass[lrate .> 2] .= 1
pclass[lrate .> 3] .= 2;
```



```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
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[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble_hi - ensemble_lo # Lyapunov rate
pclass = Array{Int16, 1}(undef, size(lrate)...)
fill!(pclass, 0)
pclass[lrate .> 2] .= 1
pclass[lrate .> 3] .= 2;

model = Chain(
  Dense(N_coord => N_neuron, tanh),
  BatchNorm(N_neuron),
  Dense(N_neuron => N_class),
  softmax
) |> gpu # move model to GPU, if available

[30]: Chain(
  Dense(2 => 8, tanh), # 24 parameters
  BatchNorm(8), # 16 parameters, plus 16
  Dense(8 => 3), # 27 parameters
  NNlib.softmax,
) # Total: 6 trainable arrays, 67 parameters,
# plus 2 non-trainable, 16 parameters, summarysize 1.266 KiB.

[31]: # The model encapsulates parameters, randomly initialised. Its initial output is:
out1 = model(pcoord |> gpu) |> cpu # 2xN Matrix{Float32}

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0.30174 0.292602 0.286916 0.283165 ... 0.401954 0.436592 0.44925
0.291435 0.260622 0.244021 0.235257 0.362114 0.384997 0.391649
0.406825 0.446776 0.469063 0.481578 0.235932 0.17841 0.159102

[32]: # To train the model, we use batches of 128 samples, and one-hot encoding:
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
loader = Flux.DataLoader(pcoord, target) |> gpu batchsize=128 shuffle=true;

Simple 2 6 master Julia 1.9.4 CI/NN-Enabled Idle Mem: 6.75 GB Mode: Command Ln 1 Col 1 Julia ML Experiments.ipynb 0
```



Define a (simple) Neural Network Model

```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
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[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble hi - ensemble lo # Lvapunov rate
```

```
[30]: N_coord = 2
      N_class = 3
      N_neuron = 8
```

```
model = Chain(
    Dense(N_coord => N_neuron, tanh),
    BatchNorm(N_neuron),
    Dense(N_neuron => N_class),
    softmax
) |> gpu # move model to GPU, if available
```

```
[30]: Chain(
    Dense(2 => 8, tanh), # 24 parameters
    BatchNorm(8), # 16 parameters, plus 16
    Dense(8 => 3), # 27 parameters
    NNlib.softmax,
) # Total: 6 trainable arrays, 67 parameters,
# plus 2 non-trainable, 16 parameters, summarysize 1.266 KiB.
```

```
[32]: # To train the model, we use batches of 128 samples, and one-hot encoding:
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
loader = Flux.DataLoader(pcoord, target) |> gpu batchsize=128 shuffle=true
```



Chain conveniently chains together layers. Ingests a 2D (position, velocity) vector, outputs 3D class probability vector

Use |> gpu and |> cpu to Move Data

```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 📄 ▶ ■ ↺ ⏪ Code git Julia 1.9.4 CUNN-Enabled

[29]: # Phase-space coordinate
pcoord = hcat(positions, velocities) |> transpose
# Phase-space class
lrate = ensemble_hi - ensemble_lo # Lyapunov rate
pclass = Array{Int16, 1}(undef, size(lrate)...)
fill!(pclass, 0)
pclass[lrate .> 2] .= 1
pclass[lrate .> 3] .= 2;

[30]: N_coord = 2
N_class = 3
N_neuron = 8

model = Chain(
  Dense(N_coord => N_neuron, tanh),
  BatchNorm(N_neuron),
  Dense(N_neuron => N_class),
  softmax
) |> gpu # move model to GPU, if available

[30]: Chain(
  Dense(2 => 8, tanh), # 24 parameters
  BatchNorm(8), # 16 parameters, plus 16
```

```
# The model encapsulates parameters, randomly initialised. Its initial output is:
```

```
out1 = model(pcoord |> gpu) |> cpu # 2xN Matrix{Float32}
```

```
3x833 Matrix{Float32}:
```

```
0.30174 0.292602 0.286916 0.283165 ... 0.401954 0.436592 0.44925
0.291435 0.260622 0.244021 0.235257 0.362114 0.384997 0.391649
0.406825 0.446776 0.469063 0.481578 0.235932 0.17841 0.159102
```

```
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
```

```
loader = Flux.DataLoader((pcoord, target)) |> gpu batchsize=128 shuffle=true
```



Column-major inputs.
Model outputs the
likelihoods (columns) of
each class

Train the Model

Julia ML Experiments.ipynb

```
File Edit View Run Kernel Git Tabs Settings Help
```

```
[32]: # To train the model, we use batches of 128 samples, and one-hot encoding:
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
loader = Flux.DataLoader((pcoord, target) |> gpu, batchsize=128, shuffle=true);

...

[34]: optim = Flux.setup(Flux.Adam(1e-2), model) # will store optimiser momentum, etc.

losses = []
@showprogress for epoch in 1:1_000
  for (x, y) in loader
    loss, grads = Flux.withgradient(model) do m
      # Evaluate model and loss inside gradient context:
      y_hat = m(x)
      Flux.crossentropy(y_hat, y)
    end
    Flux.update!(optim, model, grads[1])
    push!(losses, loss) # logging, outside gradient context
  end
end
```

Progress: 100% | Time: 0:00:45

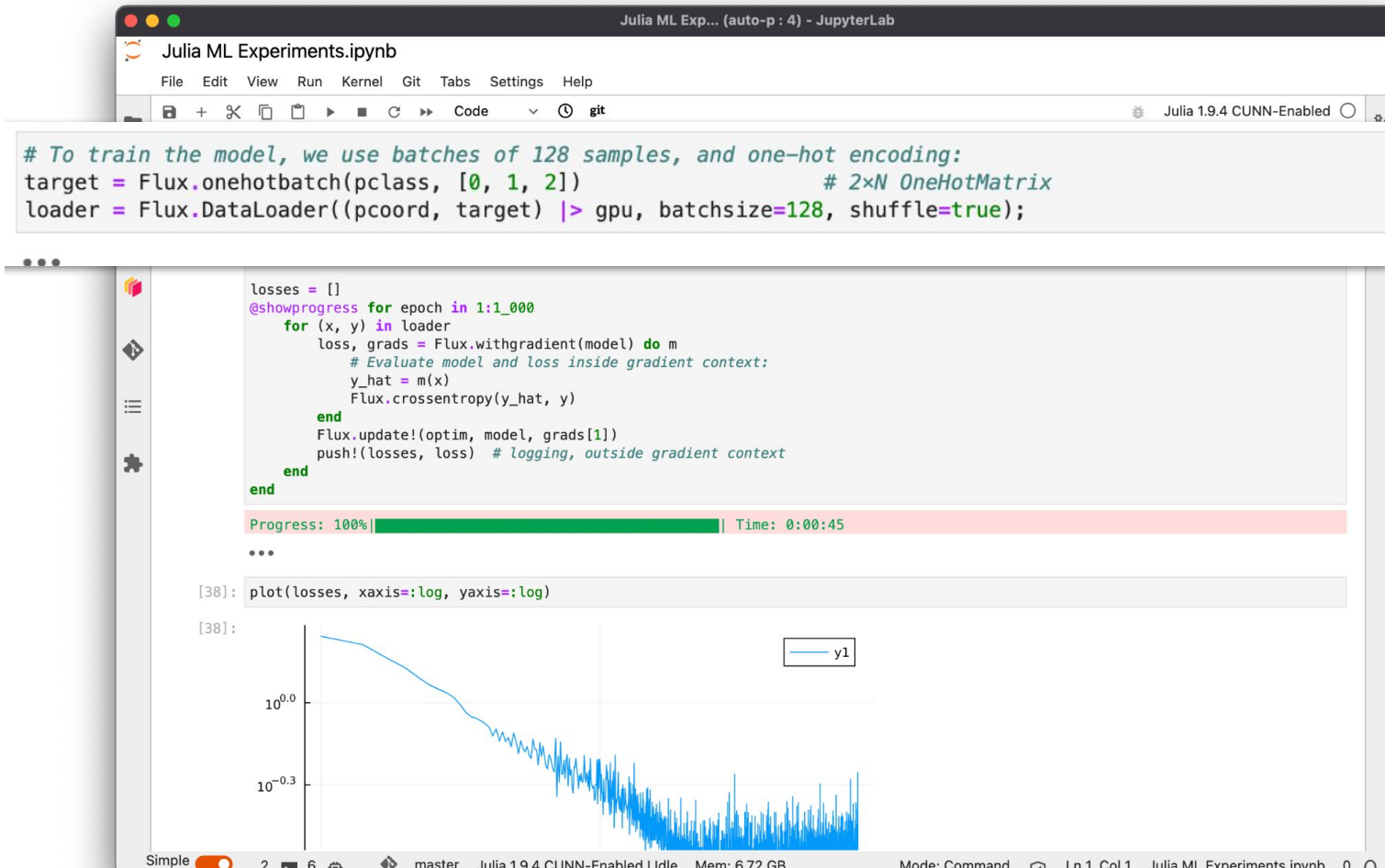
```
[38]: plot(losses, xaxis=:log, yaxis=:log)
```

[38]:

Simple 2 6 master Julia 19.4 CUNN-Enabled Idle Mem: 6.72 GB Mode: Command Ln 1 Col 1 Julia ML Experiments.ipynb

Train the Model

|> gpu also works with complex data types (tuples, vectors, structs, tuples of structs, ...)



```
Julia ML Exp... (auto-p : 4) - JupyterLab
Julia ML Experiments.ipynb
File Edit View Run Kernel Git Tabs Settings Help
Code git Julia 1.9.4 CUNN-Enabled

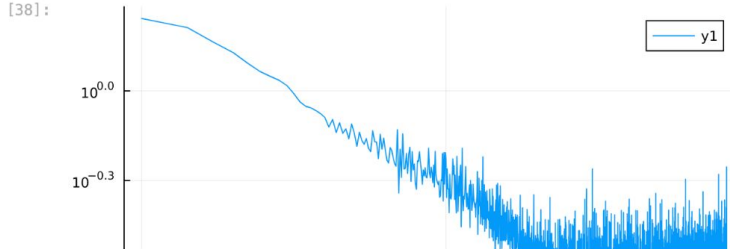
# To train the model, we use batches of 128 samples, and one-hot encoding:
target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2xN OneHotMatrix
loader = Flux.DataLoader((pcoord, target) |> gpu, batchsize=128, shuffle=true);

losses = []
@showprogress for epoch in 1:1_000
  for (x, y) in loader
    loss, grads = Flux.withgradient(model) do m
      # Evaluate model and loss inside gradient context:
      y_hat = m(x)
      Flux.crossentropy(y_hat, y)
    end
    Flux.update!(optim, model, grads[1])
    push!(losses, loss) # logging, outside gradient context
  end
end

Progress: 100% | Time: 0:00:45

...

[38]: plot(losses, xaxis=:log, yaxis=:log)
[38]:
```



Train the Model

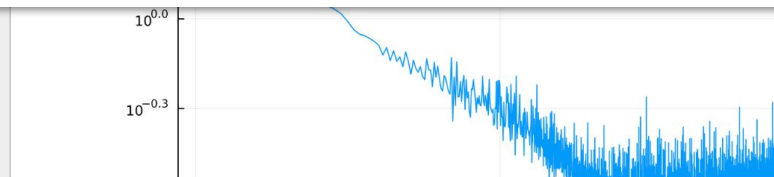
```
Julia ML Exp... (auto-p: 4) - JupyterLab
Julia ML Experiments.ipynb
File Edit View Run Kernel Git Tabs Settings Help
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```

```
[32]: # To train the model, we use batches of 128 samples, and one-hot encoding:
      target = Flux.onehotbatch(pclass, [0, 1, 2]) # 2×N OneHotMatrix
      loader = Flux.DataLoader((pcoord, target) |> gpu, batchsize=128, shuffle=true);
```

```
[34]: optim = Flux.setup(Flux.Adam(1e-2), model) # will store optimiser momentum, etc.
```

```
losses = []
@showprogress for epoch in 1:1_000
  for (x, y) in loader
    loss, grads = Flux.withgradient(model) do m
      # Evaluate model and loss inside gradient context:
      y_hat = m(x)
      Flux.crossentropy(y_hat, y)
    end
    Flux.update!(optim, model, grads[1])
    push!(losses, loss) # logging, outside gradient context
  end
end
```

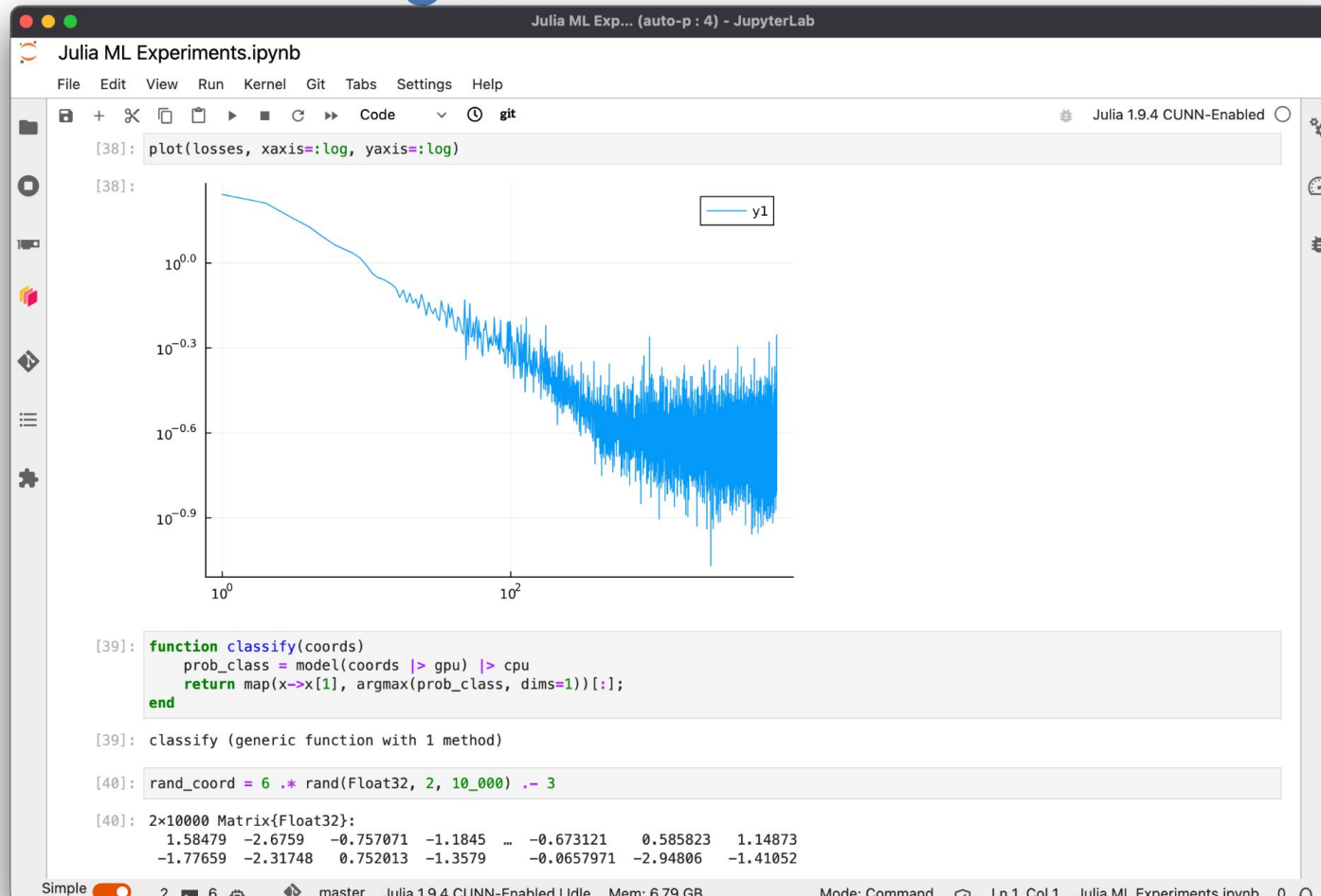
Progress: 100% | Time: 0:00:45



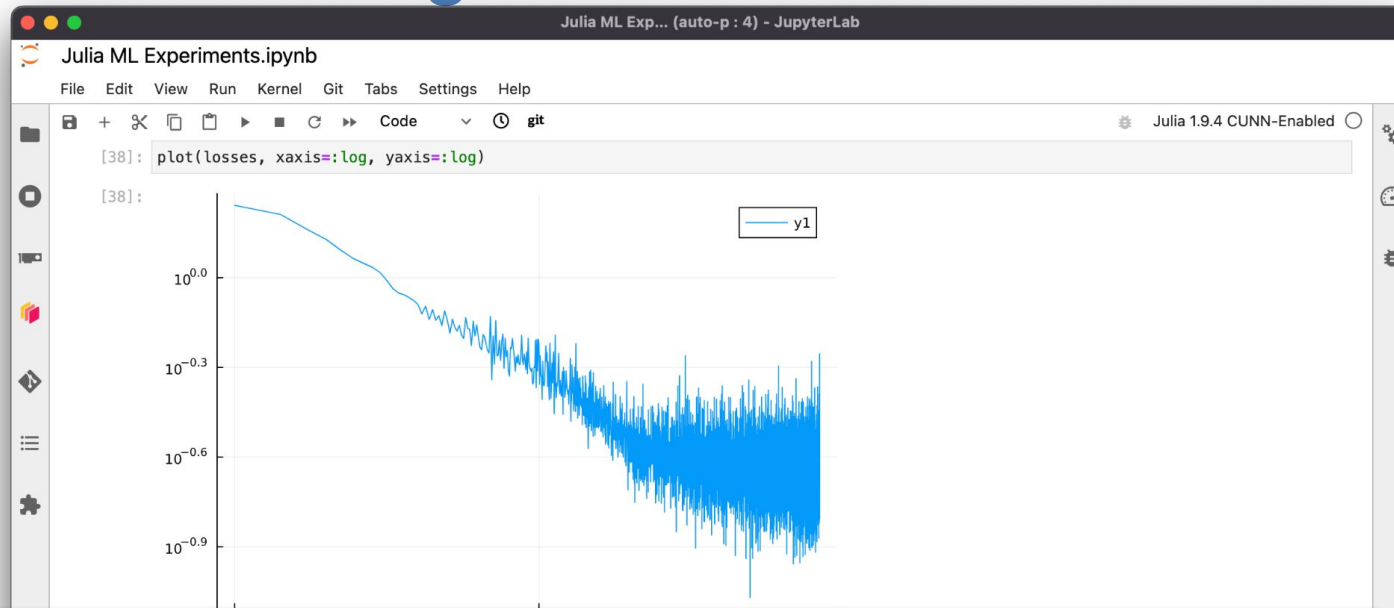
Flux.train!(model,
loader, optim)
does all of this



We've Finished Building our AI Classifier



We've Finished Building our AI Classifier



```
[39]: function classify(coords)
      prob_class = model(coords |> gpu) |> cpu
      return map(x->x[1], argmax(prob_class, dims=1))[:];
      end
```

```
[40]: rand_coord = 6 .* rand(Float32, 2, 10_000) .- 3
```

```
[40]: 2x10000 Matrix{Float32}:
      1.58479  -2.6759  -0.757071  -1.1845  ...  -0.673121  0.585823  1.14873
      -1.77659  -2.31748  0.752013  -1.3579  ...  -0.0657971  -2.94806  -1.41052
```

ML Model Infers

Julia ML Experiments.ipynb

```
File Edit View Run Kernel Git Tabs Settings Help
```

```
[39]: function classify(coords)
      prob_class = model(coords |> gpu) |> cpu
      return map(x->x[1], argmax(prob_class, dims=1))[:];
      end
```

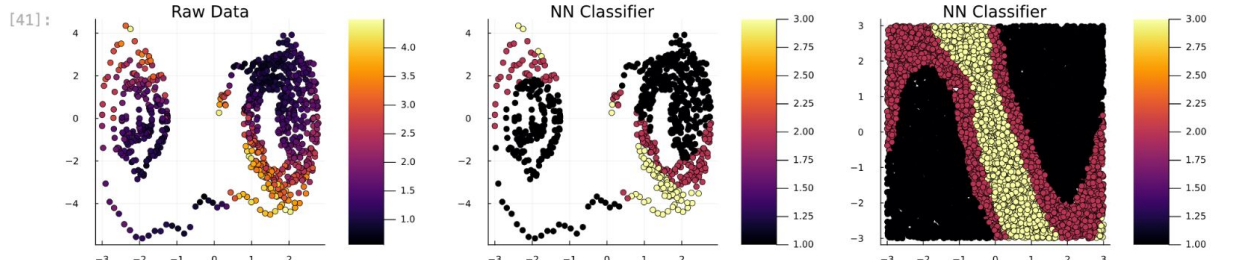
```
[39]: classify (generic function with 1 method)
```

```
[40]: rand_coord = 6 .* rand(Float32, 2, 10_000) .- 3
```

```
[40]: 2×10000 Matrix{Float32}:
      1.58479 -2.6759 -0.757071 -1.1845 ... -0.673121 0.585823 1.14873
      -1.77659 -2.31748 0.752013 -1.3579 -0.0657971 -2.94806 -1.41052
```

```
[41]: p_true = scatter(pcoord[1, :], pcoord[2, :], zcolor=:lrate, title="Raw Data")
      p_nn = scatter(pcoord[1, :], pcoord[2, :], zcolor=:classify(pcoord), title="NN Classifier")
      p_rand = scatter(rand_coord[1, :], rand_coord[2, :], zcolor=:classify(rand_coord), title="NN Classifier")
      plot(p_true, p_nn, p_rand, layout=(1,3), size=(1500,330), legend=false)
```

[41]:



The figure displays three scatter plots side-by-side, each with a color bar on its right. The first plot, titled "Raw Data", shows two distinct clusters of points in a 2D space, colored by a variable ranging from 1.0 to 4.0. The second plot, titled "NN Classifier", shows the same two clusters, but the points are colored based on the classifier's output, showing a clear separation between the two classes. The third plot, titled "NN Classifier", shows the same two clusters, but the points are colored based on a random classifier's output, resulting in a noisy, mixed distribution of colors across the clusters.

Julia ML Experiments.ipynb

File Edit View Run Kernel Git Tabs Settings Help

```
[40]: rand_coord = 6 .* rand(Float32, 2, 10_000) .- 3
```

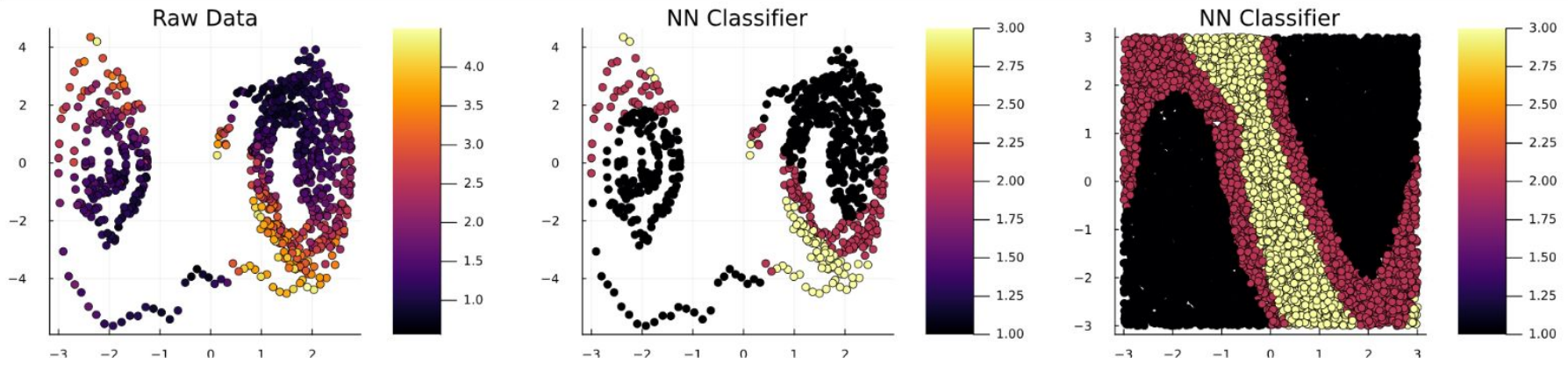
```
[40]: 2×10000 Matrix{Float32}:  
 1.58479 -2.6759 -0.757071 -1.1845 ... -0.673121 0.585823 1.14873  
-1.77659 -2.31748 0.752013 -1.3579 -0.0657971 -2.94806 -1.41052
```

```
[40]: rand_coord = 6 .* rand(Float32, 2, 10_000) .- 3
```

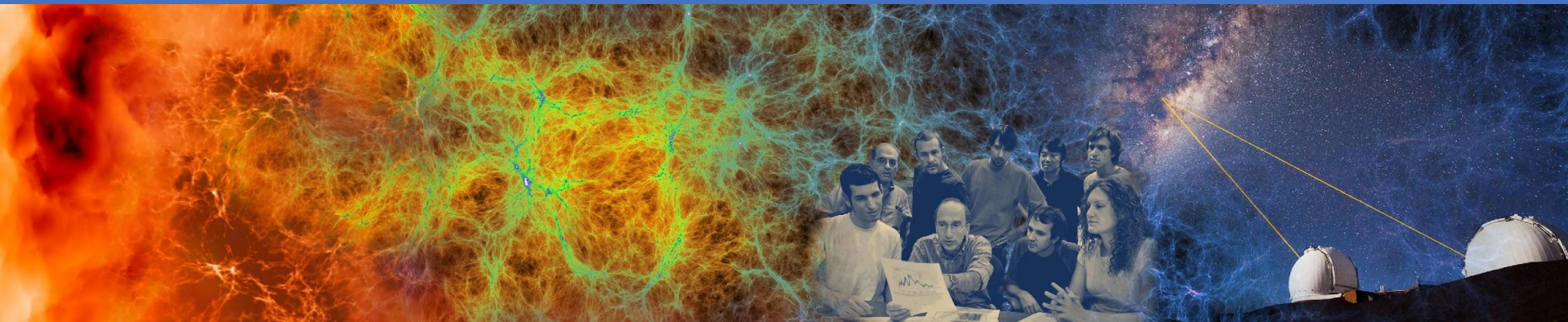
```
[40]: 2×10000 Matrix{Float32}:  
 1.58479 -2.6759 -0.757071 -1.1845 ... -0.673121 0.585823 1.14873  
-1.77659 -2.31748 0.752013 -1.3579 -0.0657971 -2.94806 -1.41052
```

```
plot(p_true, p_mn, p_rand, layout=(1,3), size=(1500,550), legend=false)
```

[41]:



Using Dagger.jl To parallelize your workflow



Dagger.jl: Easy work distribution

```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 🗑️ ▶️ ■ 🔄 ⏪ Code ⌚ git SC23 Julia 1.9.3

[1]: using Distributed, ClusterManagers, BenchmarkTools

[2]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
srun: job 18135272 queued and waiting for resources
srun: job 18135272 has been allocated resources
connecting to worker 2 out of 2

[2]: 2-element Vector{Int64}:
 2
 3

[3]: @everywhere using Dagger

[11]: darr1 = rand(Blocks(500, 500), 1_000, 1_000);
      darr2 = rand(Blocks(500, 500), 1_000, 1_000);

[12]: function test_mul()
      darr1 * darr2
      wait;
      end

[12]: test_mul (generic function with 1 method)

[13]: @benchmark(test_mul())

[13]: BenchmarkTools.Trial: 8128 samples with 1 evaluation.
Range (min ... max): 340.665 μs ... 1.253 s | GC (min ... max): 0.00% ... 87.19%
Time (median): 432.180 μs | GC (median): 0.00%
Time (mean ± σ): 612.252 μs ± 13.935 ms | GC (mean ± σ): 21.96% ± 0.97%

Histogram: frequency by time
341 μs | 676 μs <

Memory estimate: 167.05 KiB, allocs estimate: 3113.

[ ]:
```

Dagger.jl: Easy work distribution

```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 🗑️ ▶️ ⏏️ ⏪ ⏩ Code ⌚ git SC23 Julia 1.9.3
[1]: using Distributed, ClusterManagers, BenchmarkTools
[2]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
srun: job 18135272 queued and waiting for resources
srun: job 18135272 has been allocated resources
connecting to worker 2 out of 2
[3]: @everywhere using Dagger
[11]: darr1 = rand(Blocks(500, 500), 1_000, 1_000);
      darr2 = rand(Blocks(500, 500), 1_000, 1_000);
      darr1 * darr2
      wait;
      end
[12]: test_mul (generic function with 1 method)
[13]: @benchmark(test_mul())
[13]: BenchmarkTools.Trial: 8128 samples with 1 evaluation.
Range (min ... max): 340.665 μs ... 1.253 s | GC (min ... max): 0.00% ... 87.19%
Time (median): 432.180 μs | GC (median): 0.00%
Time (mean ± σ): 612.252 μs ± 13.935 ms | GC (mean ± σ): 21.96% ± 0.97%
Histogram: frequency by time
341 μs 676 μs <
Memory estimate: 167.05 KiB, allocs estimate: 3113.
[ ]:
```

Dagger.jl: Easy work distribution

```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 🗑️ ▶️ ⏏️ ⏪ ⏩ Code git SC23 Julia 1.9.3
[1]: using Distributed, ClusterManagers, BenchmarkTools
[2]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
connecting to worker 1 out of 2
sruntime: job 18135272 queued and waiting for resources
sruntime: job 18135272 has been allocated resources
connecting to worker 2 out of 2
[2]: 2-element Vector{Int64}:
      2
      3
[3]: @everywhere using Dagger
[11]: darr1 = rand(Blocks(500, 500), 1_000, 1_000);
[12]: function test_mul()
      darr1 * darr2
      wait;
      end
[13]: BenchmarkTools.Trial: 8128 samples with 1 evaluation.
Range (min ... max): 340.665 μs ... 1.253 s | GC (min ... max): 0.00% ... 87.19%
Time (median): 432.180 μs | GC (median): 0.00%
Time (mean ± σ): 612.252 μs ± 13.935 ms | GC (mean ± σ): 21.96% ± 0.97%
Histogram: frequency by time
341 μs | 676 μs <
Memory estimate: 167.05 KiB, allocs estimate: 3113.
[ ]:
```

Dagger.jl: Easy work distribution

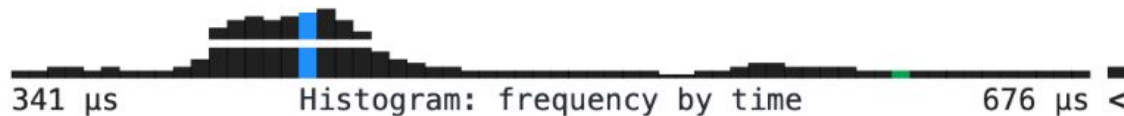
```
SC23.ipynb (11) - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
+ ✂ 📄 🗑️ ▶️ ⏪ ⏩ Code ⌚ git SC23 Julia 1.9.3
[1]: using Distributed, ClusterManagers, BenchmarkTools
[2]: addprocs(SlurmManager(2), N="2", constrain="cpu", qos="interactive", time="00:15:00", A="nstaff")
    connecting to worker 1 out of 2
    srun: job 18135272 queued and waiting for resources
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[2]: 2-element Vector{Int64}:
     2
     3
[3]: @everywhere using Dagger
[11]: darr1 = rand(Blocks(500, 500), 1_000, 1_000);
     darr2 = rand(Blocks(500, 500), 1_000, 1_000);
```

```
[13]: @benchmark(test_mul())
```

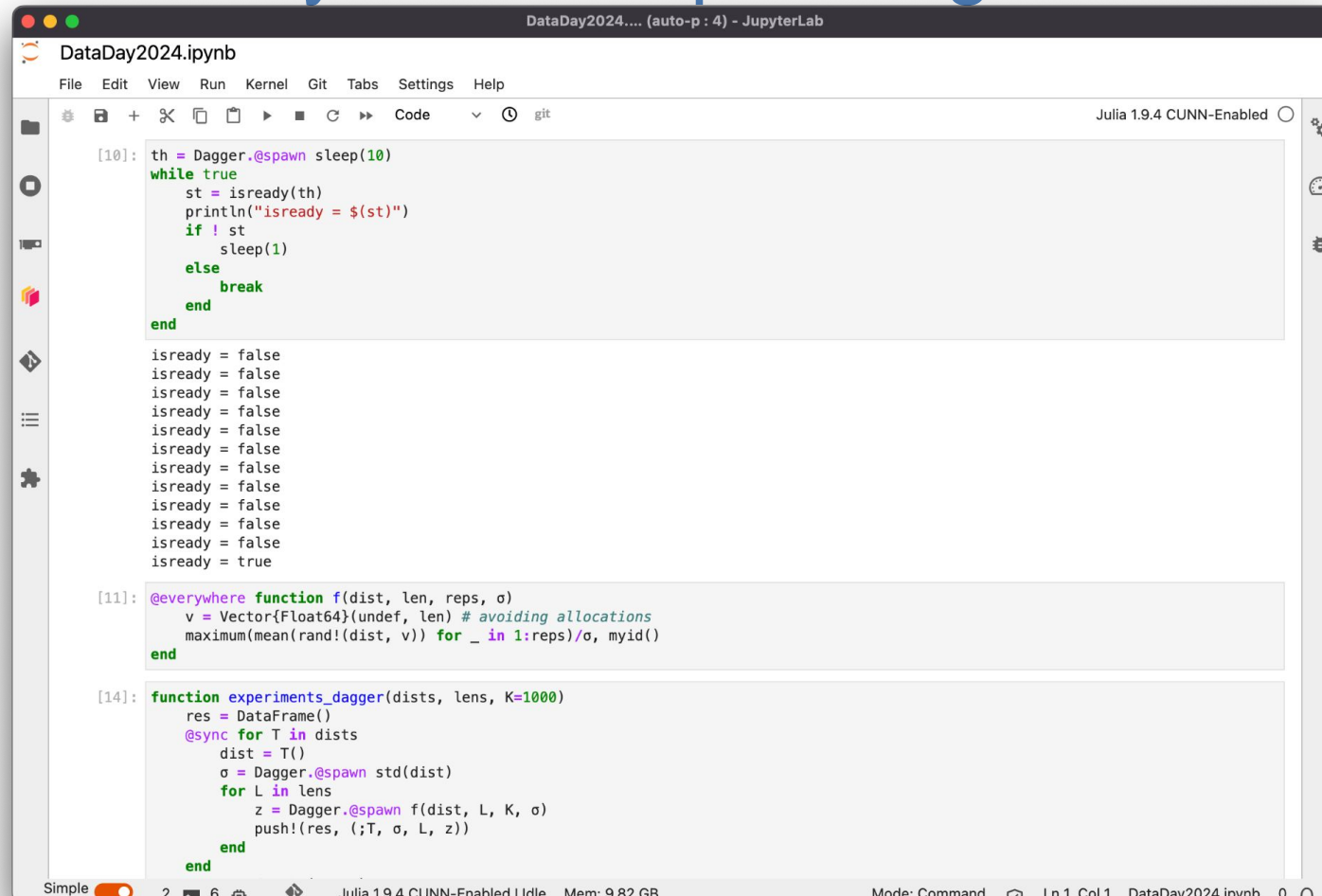
```
[13]: BenchmarkTools.Trial: 8128 samples with 1 evaluation.
```

Range (min ... max):	340.665 μ s ... 1.253 s	GC (min ... max):	0.00% ... 87.19%
Time (median):	432.180 μ s	GC (median):	0.00%
Time (mean \pm σ):	612.252 μ s \pm 13.935 ms	GC (mean \pm σ):	21.96% \pm 0.97%

For references: openBLAS
(single node) = 3.15ms,
cuBLAS = 121 μ s



Dagger Provides Async Task Spawning



The screenshot shows a JupyterLab notebook titled "DataDay2024.ipynb" with the following code:

```
[10]: th = Dagger.@spawn sleep(10)
while true
    st = isready(th)
    println("isready = $(st)")
    if ! st
        sleep(1)
    else
        break
    end
end

isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = true

[11]: @everywhere function f(dist, len, reps, σ)
    v = Vector{Float64}(undef, len) # avoiding allocations
    maximum(mean(rand!(dist, v)) for _ in 1:reps)/σ, myid()
end

[14]: function experiments_dagger(dists, lens, K=1000)
    res = DataFrame()
    @sync for T in dists
        dist = T()
        σ = Dagger.@spawn std(dist)
        for L in lens
            z = Dagger.@spawn f(dist, L, K, σ)
            push!(res, (;T, σ, L, z))
        end
    end
end
```

The notebook interface includes a menu bar (File, Edit, View, Run, Kernel, Git, Tabs, Settings, Help), a toolbar with icons for file operations and execution, and a status bar at the bottom showing "Julia 1.9.4 CUNN-Enabled" and "Mem: 9.82 GB".



Dagger Provides Async Task Spawning

Tasks start immediately.
Spawning is non-blocking.
This is called `EagerThunk`

```
[10]: th = Dagger.@spawn sleep(10)
      while true
        st = isready(th)
        println("isready = $(st)")
        if ! st
            sleep(1)
        else
            break
        end
      end
end
```

```
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = true
```

```
[14]: function experiments_dagger(dists, lens, K=1000)
      res = DataFrame()
      @sync for T in dists
        dist = T()
        σ = Dagger.@spawn std(dist)
        for L in lens
          z = Dagger.@spawn f(dist, L, K, σ)
          push!(res, (;T, σ, L, z))
        end
      end
end
```



Dagger Provides Async Task Spawning

```
DataDay2024.ipynb
File Edit View Run Kernel Git Tabs Settings Help
Julia 1.9.4 CUNN-Enabled

[10]: th = Dagger.@spawn sleep(10)
      while true
      st = isready(th)
      println("isready = $(st)")
      if ! st
      sleep(1)
      else
      break
      end
      end

isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false

[11]: @everywhere function f(dist, len, reps, σ)
      v = Vector{Float64}(undef, len) # avoiding allocations
      maximum(mean(rand!(dist, v) for _ in 1:reps)/σ, myid())
      end

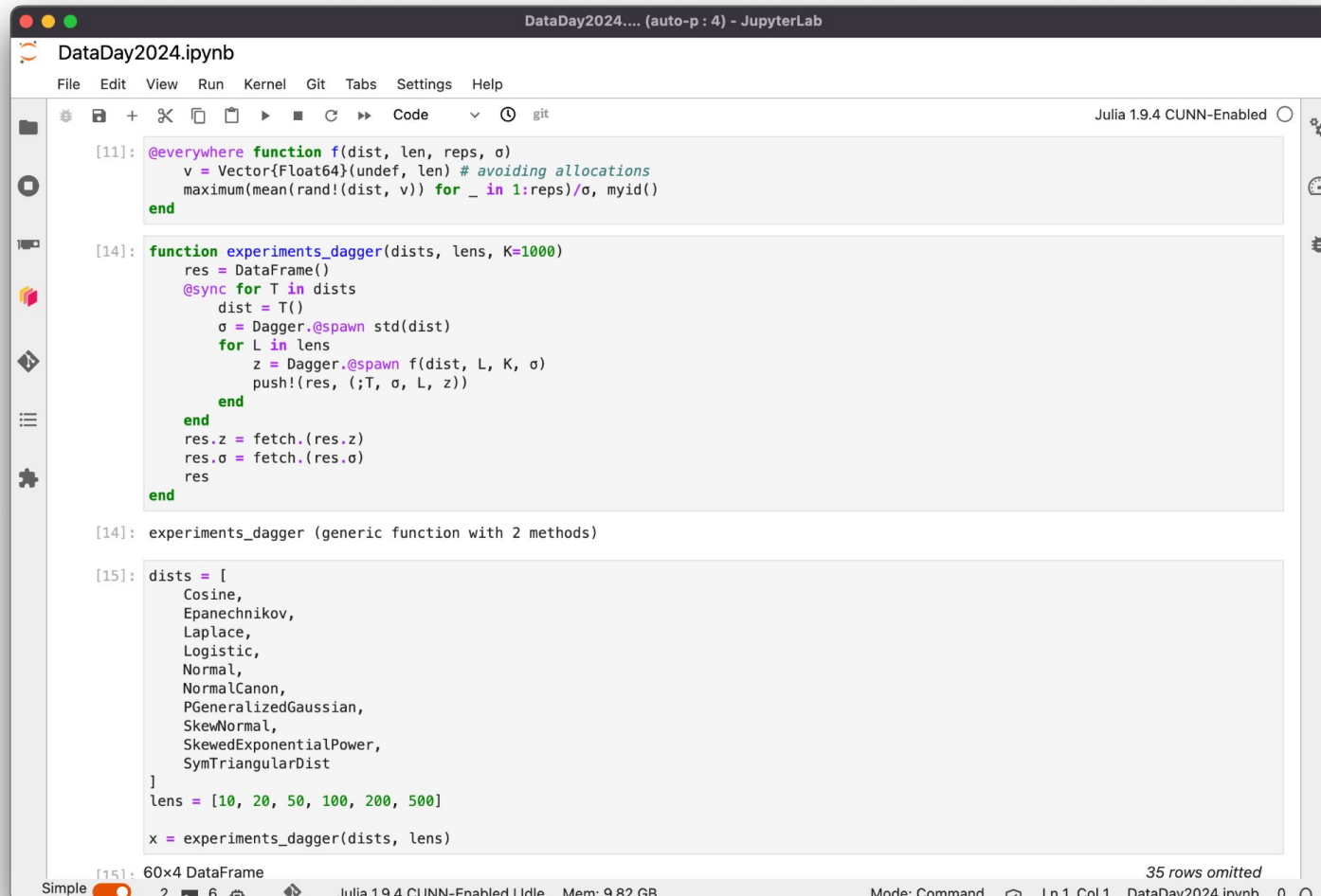
[14]: function experiments_dagger(dists, lens, K=1000)
      res = DataFrame()
      @sync for T in dists
      dist = T()
      σ = Dagger.@spawn std(dist)
      for L in lens
      z = Dagger.@spawn f(dist, L, K, σ)
      push!(res, (;T, σ, L, z))
      end
      end
      end
```

Track where the function runs

Functions to be used by
@spawn need to be defined
with @everywhere



Use Loop to Submit Tasks to Workers



```
DataDay2024.ipynb
File Edit View Run Kernel Git Tabs Settings Help
Julia 1.9.4 CUNN-Enabled

[11]: @everywhere function f(dist, len, reps, σ)
      v = Vector{Float64}(undef, len) # avoiding allocations
      maximum(mean(rand!(dist, v)) for _ in 1:reps)/σ, myid()
      end

[14]: function experiments_dagger(dists, lens, K=1000)
      res = DataFrame()
      @sync for T in dists
          dist = T()
          σ = Dagger.@spawn std(dist)
          for L in lens
              z = Dagger.@spawn f(dist, L, K, σ)
              push!(res, (;T, σ, L, z))
          end
      end
      res.z = fetch.(res.z)
      res.σ = fetch.(res.σ)
      res
      end

[14]: experiments_dagger (generic function with 2 methods)

[15]: dists = [
      Cosine,
      Epanechnikov,
      Laplace,
      Logistic,
      Normal,
      NormalCanon,
      PGeneralizedGaussian,
      SkewNormal,
      SkewedExponentialPower,
      SymTriangularDist
      ]
      lens = [10, 20, 50, 100, 200, 500]
      x = experiments_dagger(dists, lens)

[15]: 60x4 DataFrame
      35 rows omitted
      Simple 2 6 4 Julia 1.9.4 CUNN-Enabled Idle Mem: 9.82 GB Mode: Command Ln 1 Col 1 DataDay2024.ipynb 0
```



Use Loop to Submit Tasks to Workers

```
DataDay2024.ipynb
File Edit View Run Kernel Git Tabs Settings Help
Code git Julia 1.9.4 CUNN-Enabled
```

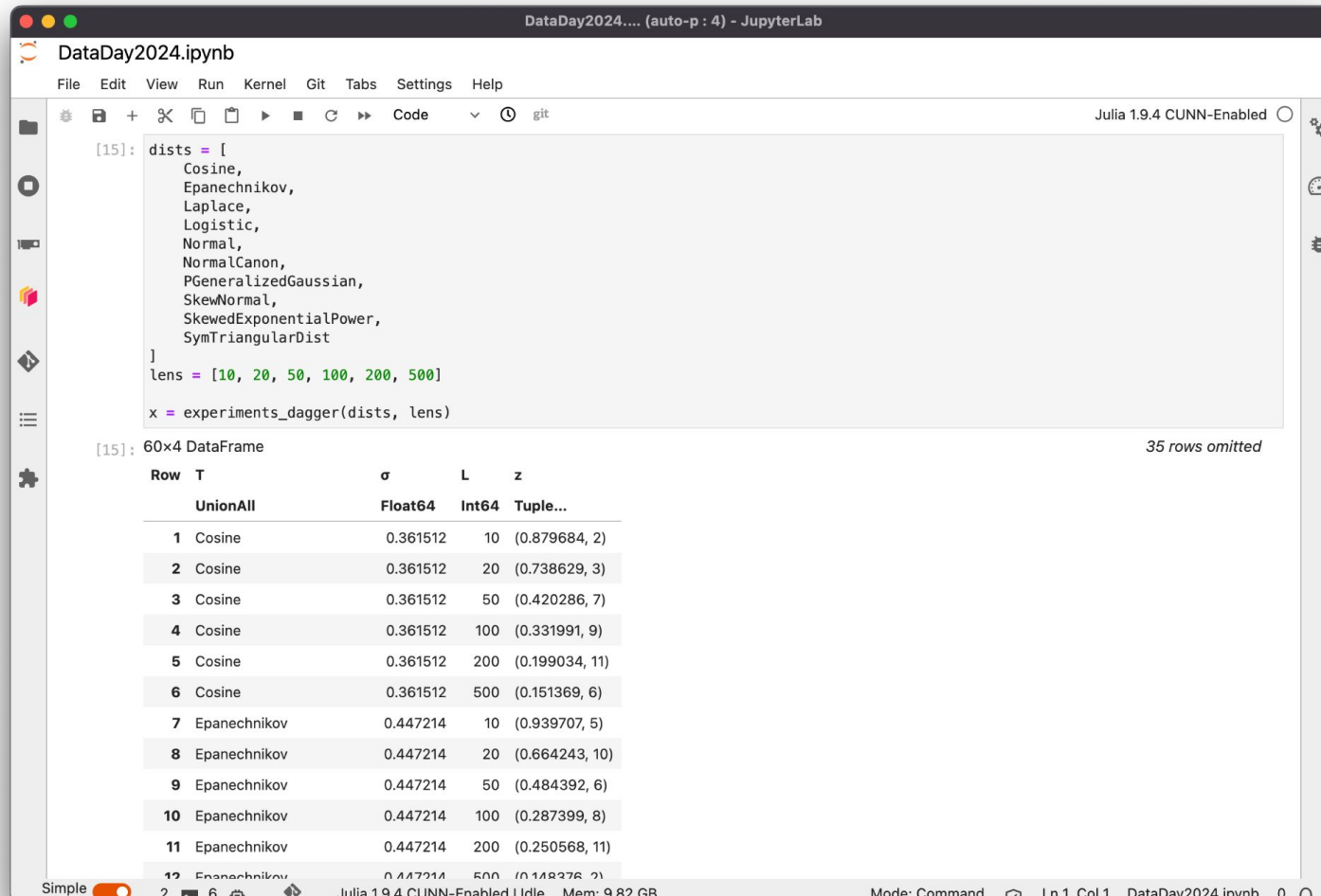
```
[14]: function experiments_dagger(dists, lens, K=1000)
      res = DataFrame()
      @sync for T in dists
          dist = T()
           $\sigma$  = Dagger.@spawn std(dist)
          for L in lens
              z = Dagger.@spawn f(dist, L, K,  $\sigma$ )
              push!(res, (;T,  $\sigma$ , L, z))
          end
      end
      res.z = fetch.(res.z)
      res. $\sigma$  = fetch.(res. $\sigma$ )
      res
  end
```

@spawn is non-blocking,
fetch or using a variable
are blocking

```
[15]: dists = [
      Cosine,
      Epanechnikov,
      Laplace,
      Logistic,
      Normal,
      NormalCanon,
      PGeneralizedGaussian,
      SkewNormal,
      SkewedExponentialPower,
      SymTriangularDist
    ]
      lens = [10, 20, 50, 100, 200, 500]
      x = experiments_dagger(dists, lens)
```



Where Did All The Tasks Run?



The screenshot shows a JupyterLab notebook titled "DataDay2024.ipynb" running Julia 1.9.4. The code defines a list of distributions and lens values, then calls a function to generate a DataFrame. The output is a 60x4 DataFrame with columns Row, T, σ , L, and z. The first 11 rows are visible, showing a mix of Cosine and Epanechnikov distributions with varying lens values and z-scores.

```
[15]: dists = [
      Cosine,
      Epanechnikov,
      Laplace,
      Logistic,
      Normal,
      NormalCanon,
      PGeneralizedGaussian,
      SkewNormal,
      SkewedExponentialPower,
      SymTriangularDist
    ]
lens = [10, 20, 50, 100, 200, 500]

x = experiments_dagger(dists, lens)
```

[15]: 60x4 DataFrame 35 rows omitted

Row	T	σ	L	z
	UnionAll	Float64	Int64	Tuple...
1	Cosine	0.361512	10	(0.879684, 2)
2	Cosine	0.361512	20	(0.738629, 3)
3	Cosine	0.361512	50	(0.420286, 7)
4	Cosine	0.361512	100	(0.331991, 9)
5	Cosine	0.361512	200	(0.199034, 11)
6	Cosine	0.361512	500	(0.151369, 6)
7	Epanechnikov	0.447214	10	(0.939707, 5)
8	Epanechnikov	0.447214	20	(0.664243, 10)
9	Epanechnikov	0.447214	50	(0.484392, 6)
10	Epanechnikov	0.447214	100	(0.287399, 8)
11	Epanechnikov	0.447214	200	(0.250568, 11)
12	Epanechnikov	0.447214	500	(0.148376, 2)

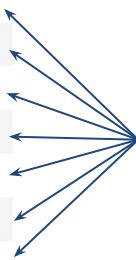
Where Did

```
[15]: dists = [
      Cosine,
      Epanechnikov,
      Laplace,
      Logistic,
      Normal,
      NormalCanon,
      PGeneralizedGaussian,
      SkewNormal,
      SkewedExponentialPower,
      SymTriangularDist
    ]
lens = [10, 20, 50, 100, 200, 500]

x = experiments_dagger(dists, lens)
```

[15]: 60x4 DataFrame

Row	T	σ	L	z
	UnionAll	Float64	Int64	Tuple...
1	Cosine	0.361512	10	(0.879684, 2)
2	Cosine	0.361512	20	(0.738629, 3)
3	Cosine	0.361512	50	(0.420286, 7)
4	Cosine	0.361512	100	(0.331991, 9)
5	Cosine	0.361512	200	(0.199034, 11)
6	Cosine	0.361512	500	(0.151369, 6)
7	Epanechnikov	0.447214	10	(0.939707, 5)
8	Epanechnikov	0.447214	20	(0.664243, 10)
9	Epanechnikov	0.447214	50	(0.484392, 6)
10	Epanechnikov	0.447214	100	(0.287399, 8)
11	Epanechnikov	0.447214	200	(0.250568, 11)



All the tasks are distributed over the Distributed.jl processors



Time to Accelerate the MC Sampler

Serial version:

1. Simulate N steps
2. Simulate `ensemble.n` independent trajectories
3. Aggregate data

```
times, positions, velocities, total_energies = baoab(
    energy, force, N*dt, dt,
    gamma, kBT, initial_position, initial_velocity;
    save_frequency=save_frequency, kwargs...
)

p_r = rand(ensemble.d, ensemble.n)
v_r = rand(ensemble.d, ensemble.n)

dtasks = Any[]
for i in 1:ensemble.n
    p = initial_position + p_r[i]
    v = initial_velocity + v_r[i]

    dtask = baoab(
        energy, force, ensemble.len*dt, dt,
        gamma, kBT, p + p_r[i], v + v_r[i];
        save_frequency=save_frequency, kwargs...
    )

    push!(dtasks, dtask)
end

ensemble_t = Array{T, 1}[]
ensemble_p = Array{T, 1}[]
for task in dtasks
    t_i, p_i, v_i, _ = task
    push!(ensemble_t, t_i + t_i)
    push!(ensemble_p, p_i)
end
```


Time to Accelerate the MC Sampler

Naive parallelization:

1. Simulate N steps
2. Spawn `ensemble.n` independent trajectory simulation tasks
3. Fetch data

```
times, positions, velocities, total_energies = baoab(
    energy, force, N*dt, dt,
    gamma, kBT, initial_position, initial_velocity;
    save_frequency=save_frequency, kwargs...
)

p_r = rand(ensemble.d, ensemble.n)
v_r = rand(ensemble.d, ensemble.n)

dtasks = Dagger.EagerThink[]
@sync for i in 1:ensemble.n
    p = initial_position + p_r[i]
    v = initial_velocity + v_r[i]

    dtask = Dagger.@spawn baoab(
        energy, force, ensemble.len*dt, dt,
        gamma, kBT, p + p_r[i], v + v_r[i];
        save_frequency=save_frequency, kwargs...
    )

    push!(dtasks, dtask)
end

ensemble_t = Array{T, 1}[]
ensemble_p = Array{T, 1}[]
for task in dtasks
    t_i, p_i, _, _ = fetch(task)
    push!(ensemble_t, t_i)
    push!(ensemble_p, p_i)
end
```

There is No Free Lunch

DataDay2024_3.ipynb

File Edit View Run Kernel Git Tabs Settings Help

Code git Julia 1.9.4 CUNN-Enabled

```
[220]: @benchmark integrate_ensemble(4, initial_position, initial_velocity)
```

[220]: BenchmarkTools.Trial: 100 samples with 1 evaluation.
Range (min ... max): 46.908 ms ... 58.275 ms | GC (min ... max): 14.97% ... 26.60%
Time (median): 49.374 ms | GC (median): 16.31%
Time (mean ± σ): 50.150 ms ± 2.361 ms | GC (mean ± σ): 16.60% ± 2.01%

46.9 ms Histogram: frequency by time 56.8 ms <

Memory estimate: 55.27 MiB, allocs estimate: 861963.

```
[221]: @benchmark integrate_ensemble_dagger_1(4, initial_position, initial_velocity)
```

[221]: BenchmarkTools.Trial: 3 samples with 1 evaluation.
Range (min ... max): 2.131 s ... 2.185 s | GC (min ... max): 6.53% ... 10.35%
Time (median): 2.131 s | GC (median): 8.76%
Time (mean ± σ): 2.149 s ± 31.165 ms | GC (mean ± σ): 8.56% ± 1.92%

2.13 s Histogram: frequency by time 2.18 s <

Memory estimate: 264.10 MiB, allocs estimate: 4976193.

```
[222]: @benchmark integrate_ensemble_dagger_2(4, initial_position, initial_velocity)
```

[222]: BenchmarkTools.Trial: 164 samples with 1 evaluation.
Range (min ... max): 24.207 ms ... 77.653 ms | GC (min ... max): 0.00% ... 33.55%
Time (median): 26.291 ms | GC (median): 0.00%
Time (mean ± σ): 30.775 ms ± 10.293 ms | GC (mean ± σ): 5.14% ± 9.23%

24.2 ms Histogram: log(frequency) by time 65.4 ms <

Memory estimate: 3.21 MiB, allocs estimate: 62962.

Simple 2 6 Julia 1.9.4 CUNN-Enabled Idle Mem: 10.02 GB Mode: Command Ln 1, Col 2 DataDay2024_3.ipynb



There is No Free Lunch

DataDay2024_... (auto-p: 4) - JupyterLab
DataDay2024_3.ipynb

```
[220]: @benchmark integrate_ensemble(4, initial_position, initial_velocity)
```

```
[220]: BenchmarkTools.Trial: 100 samples with 1 evaluation.  
Range (min ... max): 46.908 ms ... 58.275 ms | GC (min ... max): 14.97% ... 26.60%  
Time (median): 49.374 ms | GC (median): 16.31%  
Time (mean ± σ): 50.150 ms ± 2.361 ms | GC (mean ± σ): 16.60% ± 2.01%
```



Memory estimate: 55.27 MiB, allocs estimate: 861963.

```
Range (min ... max): 2.131 s ... 2.185 s | GC (min ... max): 6.53% ... 10.35%  
Time (median): 2.131 s | GC (median): 8.76%  
Time (mean ± σ): 2.149 s ± 31.165 ms | GC (mean ± σ): 8.56% ± 1.92%
```



Memory estimate: 264.10 MiB, allocs estimate: 4976193.

```
[222]: @benchmark integrate_ensemble_dagger_2(4, initial_position, initial_velocity)
```

```
[222]: BenchmarkTools.Trial: 164 samples with 1 evaluation.  
Range (min ... max): 24.207 ms ... 77.653 ms | GC (min ... max): 0.00% ... 33.55%  
Time (median): 26.291 ms | GC (median): 0.00%  
Time (mean ± σ): 30.775 ms ± 10.293 ms | GC (mean ± σ): 5.14% ± 9.23%
```



Memory estimate: 3.21 MiB, allocs estimate: 62962.



There is No Free Lunch

DataDay2024_... (auto-p: 4) - JupyterLab
DataDay2024_3.ipynb

```
[220]: @benchmark integrate_ensemble(4, initial_position, initial_velocity)
```

```
[220]: BenchmarkTools.Trial: 100 samples with 1 evaluation.  
Range (min ... max): 46.908 ms ... 58.275 ms | GC (min ... max): 14.97% ... 26.60%  
Time (median): 49.374 ms | GC (median): 16.31%  
Time (mean ± σ): 50.150 ms ± 2.361 ms | GC (mean ± σ): 16.60% ± 2.01%
```



Memory estimate: 55.27 MiB, allocs estimate: 861963.

```
Range (min ... max): 2.131 s ... 2.185 s | GC (min ... max): 6.53% ... 10.35%  
Time (median): 2.131 s | GC (median): 8.76%
```

```
[221]: @benchmark integrate_ensemble_dagger_1(4, initial_position, initial_velocity)
```

```
[221]: BenchmarkTools.Trial: 3 samples with 1 evaluation.  
Range (min ... max): 2.131 s ... 2.185 s | GC (min ... max): 6.53% ... 10.35%  
Time (median): 2.131 s | GC (median): 8.76%  
Time (mean ± σ): 2.149 s ± 31.165 ms | GC (mean ± σ): 8.56% ± 1.92%
```



Memory estimate: 264.10 MiB, allocs estimate: 4976193.

You're not keeping workers
busy enough to amortize
@spawn costs (+too much
data movement)



Keep Workers Busy Enough

Unit of work: simulate several trajectories (or make each trajectory longer).

Don't transfer data unnecessarily:
We're only interested in how much trajectories spread out

```
@everywhere function baoab_ensemble_batch(
    energy::Function, force::Function, t, dt, batch_size,
    gamma, kBT, initial_position::T, initial_velocity::T;
    save_frequency = 3, ensemble = (len=10, d=Normal(0, 0.01), n=10),
    kwargs...
) where T <: Number

    p_r = rand(ensemble.d, batch_size)
    v_r = rand(ensemble.d, batch_size)

    dtasks = Any[]
    for i in 1:batch_size
        p = initial_position + p_r[i]
        v = initial_velocity + v_r[i]

        dtask = baoab(
            energy, force, ensemble.len*dt, dt,
            gamma, kBT, p + p_r[i], v + v_r[i];
            save_frequency=save_frequency, kwargs...
        )

        push!(dtasks, dtask)
    end

    hi_p = T[]
    lo_p = T[]
    for task in dtasks
        _, p_i, _, _ = task
        push!(hi_p, maximum(p_i))
        push!(lo_p, minimum(p_i))
    end

    return minimum(lo_p), maximum(hi_p)
end
```

Keep Workers Busy Enough

Improved parallelization:

1. Simulate N steps
2. Spawn batches of trajectory simulation tasks
3. Fetch only needed data

```
function baoab_ensemble_step_dagger_2(  
    energy::Function, force::Function, t, N, dt,  
    gamma, kBT, initial_position::T, initial_velocity::T;  
    save_frequency = 3, ensemble = (len=10, d=Normal(0, 0.01), n=10),  
    kwargs...  
) where T <: Number  
  
    times, positions, velocities, total_energies = baoab(  
        energy, force, N*dt, dt,  
        gamma, kBT, initial_position, initial_velocity;  
        save_frequency=save_frequency, kwargs...  
    )  
  
    dtasks = Dagger.EagerThunk[]  
    for i in 1:ensemble.n/ensemble.batch  
        dtask = Dagger.@spawn baoab_ensemble_batch(  
            energy, force, ensemble.len*dt, dt, ensemble.batch,  
            gamma, kBT, initial_position, initial_velocity;  
            save_frequency=save_frequency, kwargs...  
        )  
  
        push!(dtasks, dtask)  
    end  
  
    hi_p = T[]  
    lo_p = T[]  
    for task in dtasks  
        lo_p_i, hi_p_i = fetch(task)  
        append!(hi_p, hi_p_i)  
        append!(lo_p, lo_p_i)  
    end  
  
    return t .+ times, positions, velocities, total_energies, (;p_spread=maximum(hi_p)-minimum(lo_p))  
end
```

Busy Workers Amortize Overhead

DataDay2024_... (auto-p: 4) - JupyterLab
DataDay2024_3.ipynb

```
[220]: @benchmark integrate_ensemble(4, initial_position, initial_velocity)
```

```
[220]: BenchmarkTools.Trial: 100 samples with 1 evaluation.
```

```
Range (min ... max): 46.908 ms ... 58.275 ms | GC (min ... max): 14.97% ... 26.60%  
Time (median): 49.374 ms | GC (median): 16.31%  
Time (mean ± σ): 50.150 ms ± 2.361 ms | GC (mean ± σ): 16.60% ± 2.01%
```



```
Memory estimate: 55.27 MiB, allocs estimate: 861963.
```

```
Range (min ... max): 2.131 s ... 2.185 s | GC (min ... max): 6.53% ... 10.35%  
Time (median): 2.131 s | GC (median): 8.76%
```

```
[222]: @benchmark integrate_ensemble_dagger_2(4, initial_position, initial_velocity)
```

```
[222]: BenchmarkTools.Trial: 164 samples with 1 evaluation.
```

```
Range (min ... max): 24.207 ms ... 77.653 ms | GC (min ... max): 0.00% ... 33.55%  
Time (median): 26.291 ms | GC (median): 0.00%  
Time (mean ± σ): 30.775 ms ± 10.293 ms | GC (mean ± σ): 5.14% ± 9.23%
```

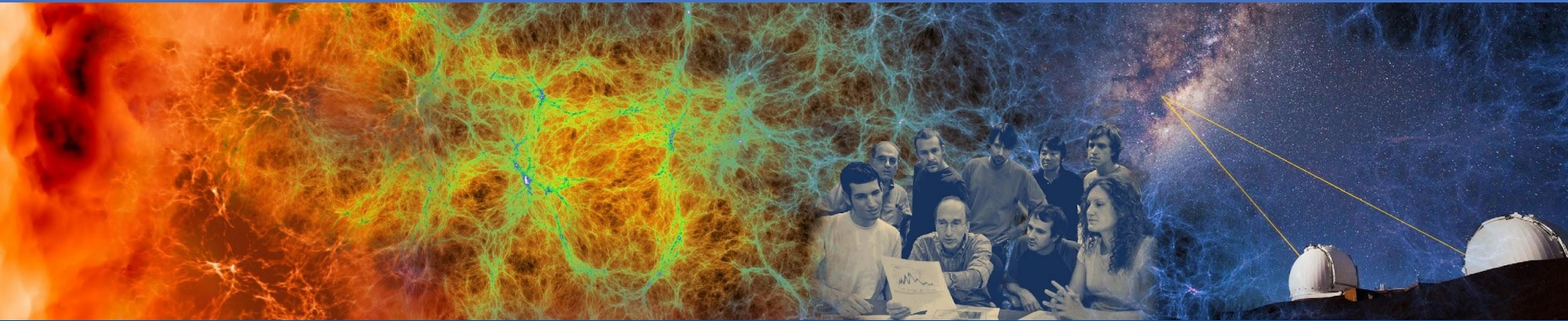


```
Memory estimate: 3.21 MiB, allocs estimate: 62962.
```

Also note: you can scale to many nodes



Conclusions



Conclusion

- Julia provides a rich ecosystem to build performant distributed applications on HPC systems
 - Saw examples of Jupyter (`IJulia.jl`); Beginnings of sophisticated multi-node workflows (`Distributed.jl`, `Dagger.jl`); Programming GPUs (`CUDA.jl`); and AI (`Flux.jl`)
- Modern high-productivity design
- HPC vendor aware. Built on top of LLVM, with vendor backends (`CUDA.jl`, `AMDGPU.jl`, `oneAPI.jl`, etc)
- Provides interfaces to examine and manipulate what you're doing (including LLVM IR)

Noteworthy Julia Packages (for HPC)

- **JuliaIO:** <https://github.com/JuliaIO>
JuliaData: <https://github.com/JuliaData>
Collects many Julia packages around I/O and Data
- **JuliaParallel:** <https://github.com/JuliaParallel>
Collects many Julia packages around distributed and parallel computing
- **JuliaGPU:** <https://github.com/JuliaGPU>
Collects many Julia packages used for GPU computing

Noteworthy I/O Packages

- **Pidfile.jl**: Provides the linux/unix pidfile mechanism to hold mutex'es – useful for locking files
- **HDF5.jl**: HDF5-file support
- **Zarr.jl**: Julia Zarr (N-D array compressed data) support
- **JLD.jl** / **JLD2.jl**: Julia-native serialization support
- **Tables.jl** / **DTables.jl** / **DistributedArrays.jl**: arrays and tables build on distributed / **CSV.jl**: Tabular data support
- **JuliaDB.jl**: A distributed database for tables (implemented in pure Julia)

Noteworthy REST and Web Frameworks

- **HTTP.jl**: Send and receive HTTP requests
- **Mux.jl / Oxygen.jl**: Routing middleware for HTTP requests – Oxygen is newer and makes multithreading easier (considered an all-Julia replacement for FastAPI)
- **Genie.jl**: Fully-fledged web development framework (Julia's answer to Flask)

Noteworthy HPC Packages

“Traditional” HPC support:

(<https://github.com/JuliaParallel>)

- **MPI.jl**: no explanation needed (it is CUDA/ROCM-aware)
- **ClusterManagers.jl**: manager HPC resources on the fly (also note **SlurmClusterManager.jl** and **MPIClusterManagers.jl** for HPC clusters)
- **ImplicitGlobalGrid.jl** / **MPIArrays.jl**: implement a global address space (using the Array interface) built on MPI.jl

Noteworthy HPC Packages

Tasking (producer-consumer) style HPC support:
(<https://github.com/JuliaParallel>)

- **Distributed.jl / Dagger.jl**: task-based parallelism (like Dask and Ray)
- **DTables.jl / DistributedArrays.jl**: arrays and tables build on distributed

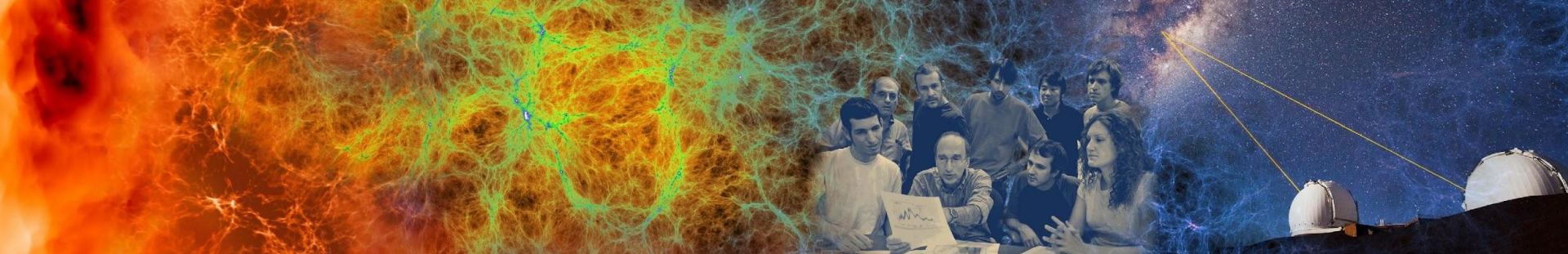
ML support: **Flux.jl** (like pytorch, but different)

Noteworthy HPC Packages

GPU Support:

(<https://github.com/JuliaGPU>)

- **CUDA.jl / AMDGPU.jl / oneAPI.jl**: low-level GPU support (expose GPU Array interface + helper functions to manage GPU resources)
- **KernelAbstractions.jl**: lets you write portable code by writing portable kernels (a bit “like” Kokkos)
- + Many Many more

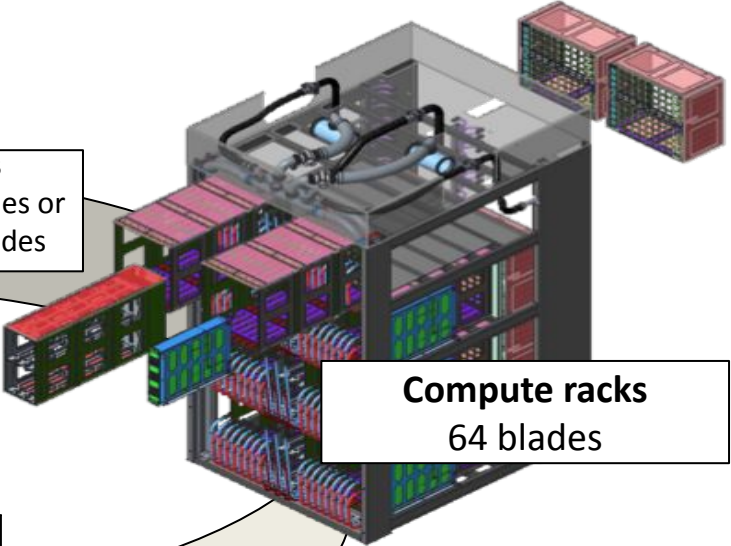
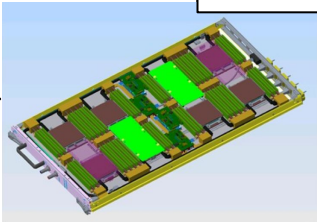
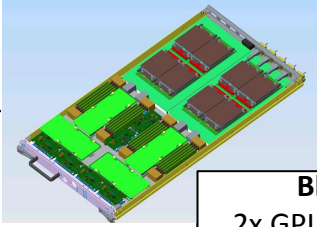


Extra Slides

Perlmutter system configuration

NVIDIA "Ampere" GPU Nodes
4x GPU + 1x CPU
40 GiB HBM + 256 GiB DDR
4x 200G "Slingshot" NICs

AMD "Milan" CPU Node
2x CPUs
> 256 GiB DDR4
1x 200G "Slingshot" NIC



Blades
2x GPU nodes or
4x CPU nodes

Compute racks
64 blades

Centers of Excellence
Network
Storage
App. Readiness
System SW

Perlmutter system
GPU racks
CPU racks
~6 MW



CUDA.jl provides detailed profiling interface

SC23.ipynb (auto-L) - JupyterLab

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+ ✂ 📄 ▶ ■ ↻ ⏪ Code ⌚ git SC23 Julia 1.9.3

```
[14]: CUDA.@profile carr1 * carr2
```

```
[14]: Profiler ran for 2.23 ms, capturing 23 events.
```

Host-side activity: calling CUDA APIs took 1.96 ms (87.81% of the trace)

Time (%)	Time	Calls	Avg time	Min time	Max time	Name	...
29.29%	653.51 μ s	1	653.51 μ s	653.51 μ s	653.51 μ s	cuMemAllo ...	
18.15%	404.83 μ s	1	404.83 μ s	404.83 μ s	404.83 μ s	cudaEvent ...	
1.12%	25.03 μ s	1	25.03 μ s	25.03 μ s	25.03 μ s	cudaLaunc ...	
0.82%	18.36 μ s	1	18.36 μ s	18.36 μ s	18.36 μ s	cudaMemse ...	
0.44%	9.78 μ s	2	4.89 μ s	953.67 ns	8.82 μ s	cudaOccup ...	
0.28%	6.2 μ s	3	2.07 μ s	476.84 ns	4.77 μ s	cudaStrea ...	
0.26%	5.72 μ s	1	5.72 μ s	5.72 μ s	5.72 μ s	cudaEvent ...	
0.00%	0.0 ns	1	0.0 ns	0.0 ns	0.0 ns	cudaGetLa ...	

1 column omitted

Device-side activity: GPU was busy for 160.22 μ s (7.18% of the trace)

Time (%)	Time	Calls	Avg time	Min time	Max time	Name	...
7.09%	158.07 μ s	1	158.07 μ s	158.07 μ s	158.07 μ s	ampere_sg ...	
0.10%	2.15 μ s	1	2.15 μ s	2.15 μ s	2.15 μ s	[set devi ...	

1 column omitted

CUDA.jl is compatible with Structs

```
SC23.ipynb [auto-L] - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help
Code git SC23 Julia 1.9.3

[17]: struct Point{T}
      x :: T
      y :: T
      end

[18]: arr = Point.(rand(100), rand(100))
      carr = cu(arr)

[18]: 100-element CuArray{Point{Float64}, 1, CUDA.Mem.DeviceBuffer}:
Point{Float64}(0.8010859437783524, 0.8642616255324465)
Point{Float64}(0.17750804805255238, 0.15240658172450294)
Point{Float64}(0.4940416892271239, 0.604324864671999)
Point{Float64}(0.8190761447346417, 0.24524461825461796)
Point{Float64}(0.8136328436633238, 0.703444856961141)
Point{Float64}(0.9014731786301712, 0.6976978604609408)
Point{Float64}(0.4734214731060712, 0.546675832272095)
Point{Float64}(0.9030369868126105, 0.5340128051286633)
Point{Float64}(0.5317337783755941, 0.8033039913403202)
Point{Float64}(0.6763381060145333, 0.6507417892793194)
Point{Float64}(0.7484751505993789, 0.748566736019653)
Point{Float64}(0.599307695857283, 0.7081606826204108)
Point{Float64}(0.4096041416396996, 0.17860717723966113)
⋮
Point{Float64}(0.8113003140580276, 0.8828241515817755)
Point{Float64}(0.13536512021293456, 0.46910612940518404)
Point{Float64}(0.9009776673421677, 0.047089614167290184)
Point{Float64}(0.7299575952344476, 0.10684973792700014)
Point{Float64}(0.0563314509491073, 0.6472313211625557)
Point{Float64}(0.18604391157970612, 0.041993134446333125)
Point{Float64}(0.9627585143646942, 0.38452121311513965)
```



CUDA.jl is compatible with Structs

Julia converts struct to cuda-compatible type

```
SC23.ipynb [auto-L] - JupyterLab
File Edit View Run Kernel Git Tabs Settings Help

[17]: struct Point{T}
      x :: T
      y :: T
      end

[18]: arr = Point.(rand(100), rand(100))
      carr = cu(arr)

Point{Float64}(0.8010859437783524, 0.8642616255324465)
Point{Float64}(0.17750804805255238, 0.15240658172450294)
Point{Float64}(0.4940416892271239, 0.604324864671999)
Point{Float64}(0.8190761447346417, 0.24524461825461796)
Point{Float64}(0.8136328436633238, 0.703444856961141)
Point{Float64}(0.9014731786301712, 0.6976978604609408)
Point{Float64}(0.4734214731060712, 0.546675832272095)
Point{Float64}(0.9030369868126105, 0.5340128051286633)
Point{Float64}(0.5317337783755941, 0.8033039913403202)
Point{Float64}(0.6763381060145333, 0.6507417892793194)
Point{Float64}(0.7484751505993789, 0.748566736019653)
Point{Float64}(0.599307695857283, 0.7081606826204108)
Point{Float64}(0.4096041416396996, 0.17860717723966113)
⋮
Point{Float64}(0.8113003140580276, 0.8828241515817755)
Point{Float64}(0.13536512021293456, 0.46910612940518404)
Point{Float64}(0.9009776673421677, 0.047089614167290184)
Point{Float64}(0.7299575952344476, 0.10684973792700014)
Point{Float64}(0.0563314509491073, 0.6472313211625557)
Point{Float64}(0.18604391157970612, 0.041993134446333125)
Point{Float64}(0.9627585143646942, 0.38452121311513965)
```





DataDay2024.... (auto-p : 4) - JupyterLab

DataDay2024.ipynb

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Julia 1.9.4 CUNN-Enabled

```
[1]: using Distributed
```

```
[2]: addprocs(10)
```

```
[2]: 10-element Vector{Int64}:
      2
      3
      4
      5
      6
      7
      8
      9
     10
     11
```

```
[3]: @everywhere using Dagger, Random, Distributions, StatsBase, DataFrames
```

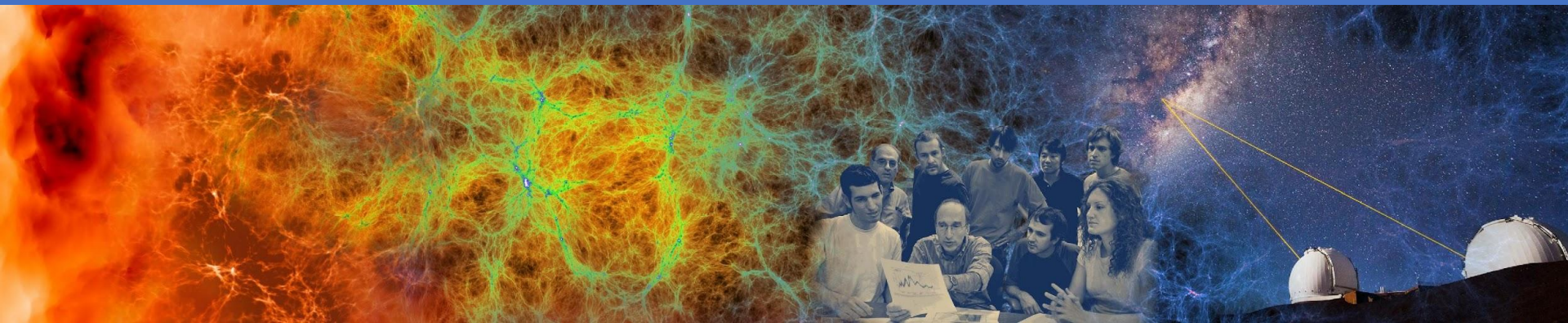
```
WARNING: using Dagger.In in module Main conflicts with an existing identifier.
WARNING: using Dagger.Out in module Main conflicts with an existing identifier.
```

```
[10]: th = Dagger.@spawn sleep(10)
      while true
          st = isready(th)
          println("isready = $(st)")
          if ! st
              sleep(1)
          else
              break
          end
      end
```

```
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
isready = false
```

Simple 2 6 4 4 Julia 1.9.4 CUNN-Enabled Idle Mem: 9.82 GB Mode: Command Ln 1 Col 1 DataDay2024.ipynb 0

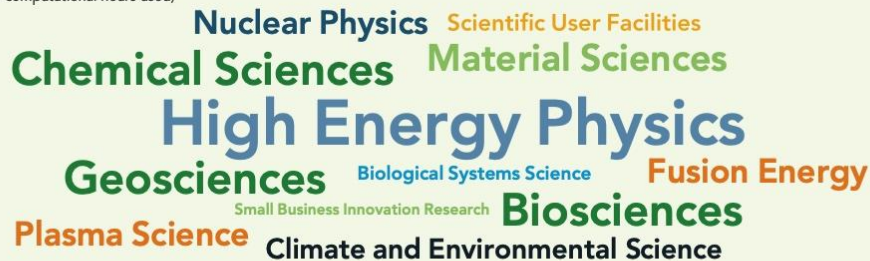
Why does NERSC care about Julia?



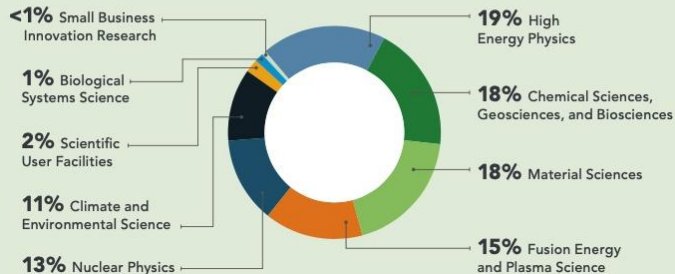
NERSC is the mission HPC and data facility for the U.S Department of Energy Office of Science

Top Science Disciplines

(By computational hours used)



Breakdown of Compute Used by DOE Program



9

NERSC BY THE NUMBERS



~9,000 ANNUAL USERS FROM ~800 Institutions + National Labs



>2,000

Scientific Journal Articles per Year



NERSC is the mission HPC and data facility for the U.S Department of Energy Office of Science

Top Science Disciplines

(By computational hours used)

Chemistry

Geosciences

Plasma Science



- Most users at NERSC are not HPC experts
 - and we can't force them to become ones
- Workflows running at NERSC are incredibly varied
 - in response, NERSC systems provide a range of capabilities
- => Julia needs to “know what to do” by default
 - Need: intelligent, easy to support, and robust interface with HPC resources

2% Scientific User Facilities

11% Climate and Environmental Science

13% Nuclear Physics

18% Material Sciences

15% Fusion Energy and Plasma Science

11% University Faculty

7% Undergraduate Students

6% Professional Staff

59% Universities

29% DOE Labs

5% Other Government Labs

3% Industry

1% Small Businesses

<1% Private Labs

>2,000

Scientific Journal Articles per Year