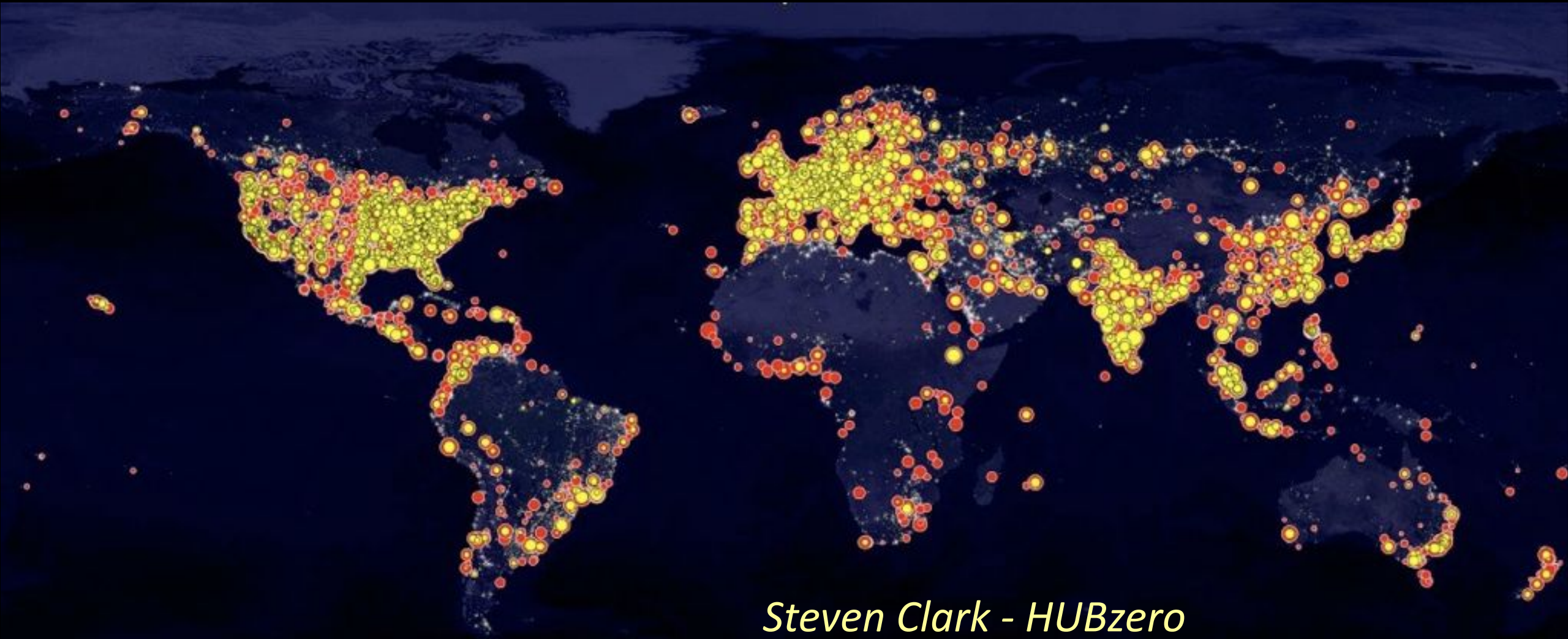


Sim2Ls: Software tools that are FAIR



Steven Clark - HUBzero
Daniel Mejia - nanoHUB
Ale Strachan - Purdue University

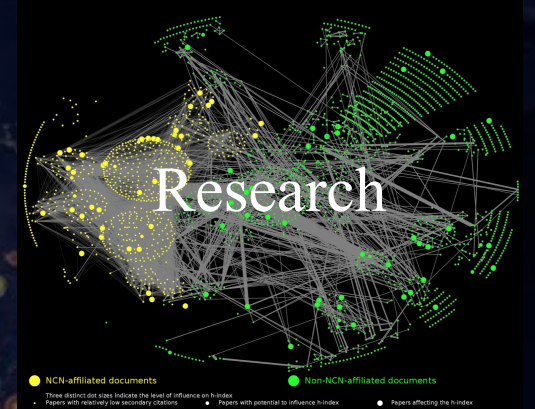
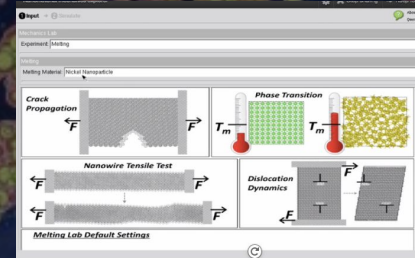
Gateways: accelerating innovation

via user-friendly, accessible apps, tools, and data

Science codes,
data tools & repos



Online Apps & Tools



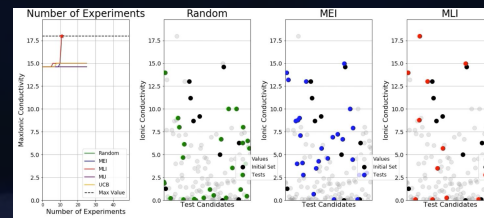
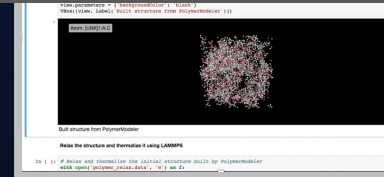
HUBzero
services

Science workflows

Sim2Ls: Modern simulation & data delivery



Data science &
machine learning



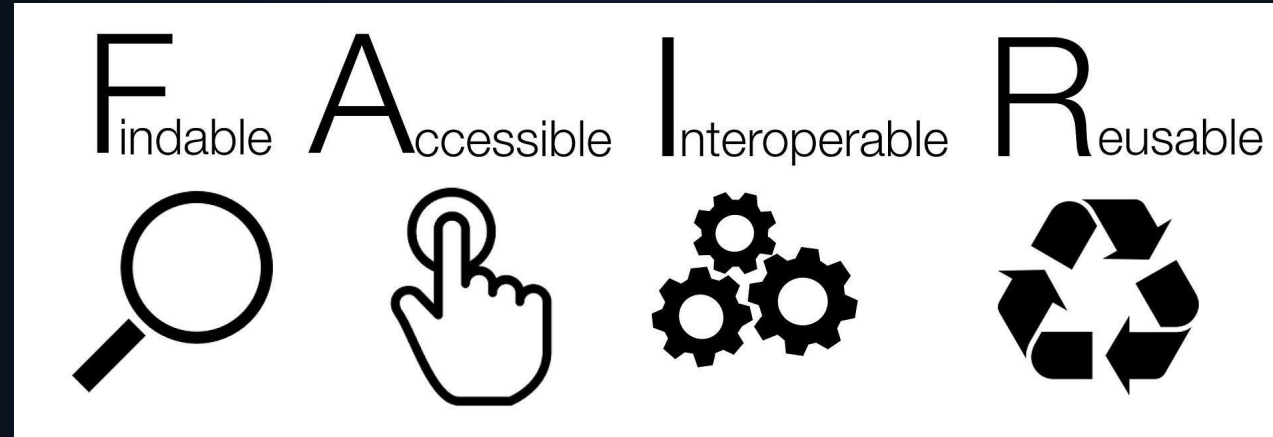
Education &
workforce
development

Users



Play FAIR

Simulation tools, associated workflows, and their results
should adhere to FAIR principles



Pundir, S. (2016) https://commons.wikimedia.org/wiki/File:FAIR_data_principles.jpg.

Findable

Data has unique identifier and is indexed in a searchable resource

Interoperable

Data uses a formal, accessible and broadly applicable language for knowledge representation

Accessible

An access protocol that is open, free and universally implementable allows for retrieval of the data

Reusable

Data is richly described with metadata for provenance and to guarantee domain-relevant community standards

FAIR principles

SCIENTIFIC DATA

Amended: Addendum

OPEN

SUBJECT CATEGORIES

» Research data

» Publication

characteristics

Comment: The FAIR Guiding

Principles for scientific
data management and

Mark D. Wilkinson *et al.*[#]

Box 2 | The FAIR Guiding Principles

To be Findable:

- F1. (meta)data are assigned a globally unique and persistent identifier
- F2. data are described with rich metadata (defined by R1 below)
- F3. metadata clearly and explicitly include the identifier of the data it describes
- F4. (meta)data are registered or indexed in a searchable resource

To be Accessible:

- A1. (meta)data are retrievable by their identifier using a standardized communications protocol
 - A1.1 the protocol is open, free, and universally implementable
 - A1.2 the protocol allows for an authentication and authorization procedure, where necessary
- A2. metadata are accessible, even when the data are no longer available

To be Interoperable:

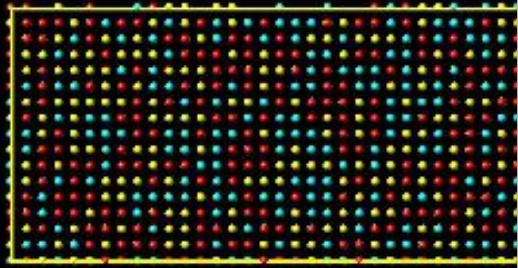
- I1. (meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation.
- I2. (meta)data use vocabularies that follow FAIR principles
- I3. (meta)data include qualified references to other (meta)data

To be Reusable:

- R1. meta(data) are richly described with a plurality of accurate and relevant attributes
 - R1.1. (meta)data are released with a clear and accessible data usage license
 - R1.2. (meta)data are associated with detailed provenance
 - R1.3. (meta)data meet domain-relevant community standards

The status quo: research workflows

1. Generate random alloy structure



2. Model to compute interactions



OpenKIM

MD to calculate the melting temperature of an alloy

Research workflows

- Are complex and involve multiple steps
- Not fully described in publications
- Often contain ad hoc scripts and manual steps

Consequently ...

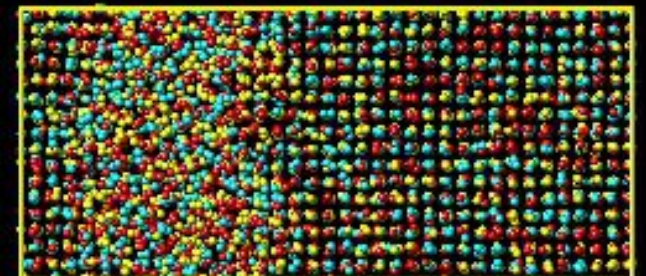
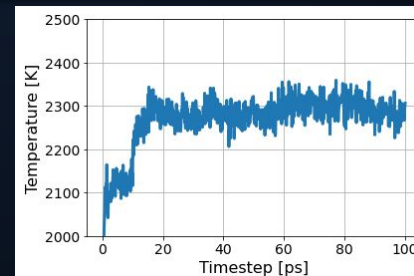
- Workflows are not findable, accessible, interoperable, or reusable
- The science generated is hard to reproduce

size phases present

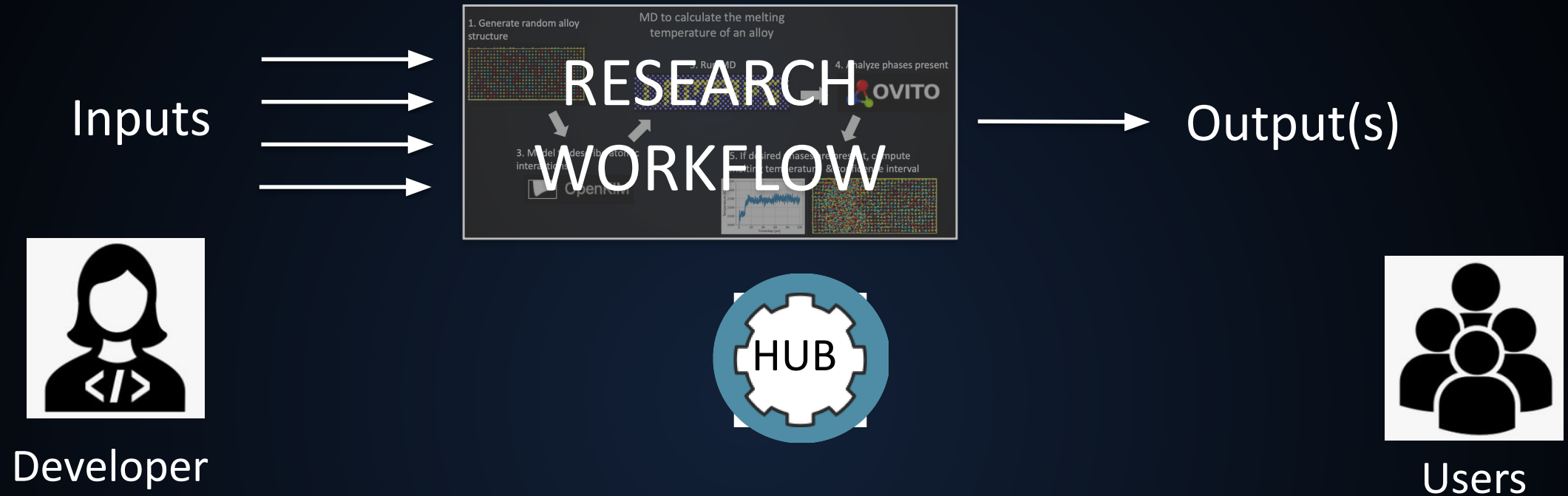
OVITO

compute

time interval



Sim2Ls: making simulation workflows FAIR



Sim2L:

- Using Jupyter notebooks
- Declare inputs & outputs (including metadata)
- Implement every step connecting INs to OUTs

Sim2L library

- Sim2Ls are registered & queryable
- Inputs and outputs (incl. metadata) are queryable
- Inputs are verified (incl. unit conversion) before run
- Outputs are checked after workflow execution
- Published Sim2Ls have DOIs & are indexed by WoS and google scholar
- Results are automatically cached & queryable (data & metadata)



Developing a Sim2L

1. Declare inputs and outputs using YAML
 - Note units, descriptions, ranges

```
In [ ]:
%%yaml INPUTS

material:
  type: Choice
  value: Ni
  options: ['Sc', 'Ti', 'V', 'Cr', 'Mn', 'Fe', 'Co', 'Ni', 'Cu', 'Zn',
            'Y', 'Zr', 'Nb', 'Mo', 'Tc', 'Ru', 'Rh', 'Pd', 'Ag', 'Cd',
            'Hf', 'Ta', 'W', 'Re', 'Os', 'Ir', 'Pt', 'Au', 'Hg']

crystal_structure:
  type: Choice
  value: fcc
  options: [fcc, bcc, hcp]

lattice_parameter:
  type: Number
  value: 3.5203
  min: 2.0
  max: 10.0
  units: angstroms

mass:
  type: Element
  property: atomic_weight
  value: Ni

Tsolid:
  type: Number
  value: 800
  min: 1
  max: 5000
  units: K
```

```
In [ ]:
%%yaml OUTPUTS

final_snapshot:
  type: Image
  description: Snapshot of the final structure (check for coexistence between liquid and solid)

melting_temperature:
  type: Number
  description: Melting temperature predicted by the simulation
  units: K

melting_temperature_ci:
  type: Number
  description: 95% confidence interval in melting temperature prediction (from the instantaneous time series)
  units: K

LAMMPS_log:
  type: Text
  description: Name of the log file written by LAMMPS

time_series:
  type: Array
  description: Instantaneous time series
  units: ps

temperature_series:
  description: Instantaneous temperature during the simulation
  type: Array
  units: K

potential_energy_series:
  type: Array
  description: Instantaneous potential energy during the simulation
  units: eV
```



Developing a Sim2L

2. Parameterization (using papermill)

```
In [ ]: parameters x

from simtool import getValidatedInputs

defaultInputs = getValidatedInputs(INPUTS)
if defaultInputs:
    globals().update(defaultInputs)
```

4. Postprocessing and save results

```
In [ ]: logfile = log(logname)
time, temperature, potential_energy, volume = logfile.get("Step", "Temp", "PotEng", "Volume")

time = np.array(time)
temperature = np.array(temperature)

#establish trend to print converged or not converged
idx = np.where(time >= 0.8*(inputs['time'] + 10000))
y = temperature[idx[0]]
x = time[idx[0]]/1000

def f(x, A, B):
    return A*x + B

popt, pcov = curve_fit(f, x, y)
slope = popt[0]
intercept = popt[1]

#fit a straight line and check for slope
if (slope > -1 and slope < 1):
    converged = True
else:
    converged = False

#report average and std deviation of melting temperature
melting_temperature = np.average(temperature[idx[0]])
melting_temperature_std = np.std(temperature[idx[0]])
melting_temperature_ci = 1.96*melting_temperature_std/np

print (melting_temperature, melting_temperature_ci, frac
```

```
In [ ]: db = DB(OUTPUTS)

In [ ]: db.save('final_snapshot', file='final.jpg')

In [ ]: db.save('melting_temperature', melting_temperature)
db.save('melting_temperature_ci', melting_temperature_ci)
db.save('fraction_solid', fraction_solid)
db.save('fraction_liquid', fraction_liquid)
db.save('counts_array', counts_array)
db.save('converged', converged)
db.save('successful', successful)

with open(logname) as fp:
    db.save('LAMMPS_log', fp.read())
```

3. Setup simulation(s) & execute

Download OpenKIM interatomic model and run LAMMPS

We setup a run script that downloads the OpenKIM interatomic model specified as SimTool input and run L

```
In [ ]: write_string = '''#!/bin/sh
lammpsInput=$1
kimModel=$2
logname=$3

. /etc/environ.sh

if [ -n "${ANACONDA_CHOICE}" ] ; then
    unset -e ${ANACONDA_CHOICE}
fi

use -e -r openkim-2.1.3
use -e -r lammps-07Aug19

downloadkim.sh ${kimModel}
#cp -r ../../EAM_* .

lmp_serial -in ${lammpsInput} -l ${logname}

'''
with open("runlammps.sh", "w") as f:
    f.write(write_string)
```




Find a Sim2L for your problem

Set up imports

We will first import the necessary libraries and packages, including the simtool package which helps locate the SimTool we wish

```
In [5]: from simtool import findSimTools, searchForSimTool
        from simtool import getSimToolInputs, getSimToolOutputs, Run

In [6]: installedSimTools = findSimTools()
        print(installedSimTools)

anngenerator:
  installed:
    r7: Creating a feed-forward ANN for datasets provided by the user
caecipher:
  installed:
    r37: null
inabstool:
  installed:
    r1: Automated workflow for computing the optical absorption of an indirect band
        gap semiconductor like Silicon, using QE and the EPW module.
introtosimtools:
  published:
    r13: Show examples of SimTool input and output types
    r8: Show examples of SimTool input and output types
    r9: Show examples of SimTool input and output types
ioexamples:
  installed:
    r6: Show examples of SimTool input and output types
mdsandbox:
  published:
    r21: '""Molecular Dynamics Ensemble Sandbox with NNRF Implementation""
        #NVE - Microcanonical: Constant Energy, Volume
        #NPT - Isothermal-Isobaric: Constant Pressure, Temperature
        #NVT - Canonical: Constant Temperature, Volume
        #NPH - Isentropic-Isobaric: Constant Pressure, Enthalpy'
meltheas:
  installed:
    r30: Computes the melting temperatures of a high entropy alloy generated by
        the user
  published:
    r20: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r21: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r23: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r24: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r27: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r33: Computes the melting temperatures of a high entropy alloy generated by
        the user
    r39: Computes the melting temperatures of a high entropy alloy generated by
        the user
meltingkim:
  published:
    r25: Computes melting point using a coexistence technique using interatomic
        potentials from OpenKIM
    r31: Computes melting point using a coexistence technique using interatomic
```

1. Explore available Sim2Ls

2. Load Sim2L of interest

SimTool information

We will first create a dictionary containing the SimTool information using the "searchForSimTool" function

```
In [3]: MeltKIM = searchForSimTool('meltingkim')
        MeltKIM

Out[3]: {'notebookPath': '/apps/meltingkim/r31/simtool/meltingkim.ipynb',
        'simToolName': 'meltingkim',
        'simToolRevision': 'r31',
        'published': True}
```



Learn Sim2L requirements & services

SimTool Inputs and Outputs

We will then create an object for the simtool inputs using the "getSimToolInputs" function - this object is validated

```
In [8]: # get the list of inputs
inputs = getSimToolInputs(MeltKIM)
print(inputs)

material:
  options: ['Sc', 'Ti', 'V', 'Cr', 'Mn', 'Fe', 'Co', 'Ni', 'Cu', 'Zn', 'Y', 'Zr',
'Ir', 'Pt', 'Au', 'Hg']
  type: Choice
  value: Ni

crystal_structure:
  options: ['fcc', 'bcc', 'hcp']
  type: Choice
  value: fcc

lattice_parameter:
  units: angstrom
  min: 2.0
  max: 10.0
  type: Number
  value: 3.5203

mass:
  type: Element
  property: atomic_weight
  value: 58.6934

Tsolid:
  units: kelvin
  min: 1
  max: 5000
  type: Number
  value: 800
```

3. Explore inputs & outputs

- Note units and types

```
In [4]: getSimToolOutputs(MeltKIM)

Out[4]: final_snapshot:
  type: Image
  description: Snapshot of the final structure (check for coexistence be

melting_temperature:
  type: Number
  description: Melting temperature predicted by the simulation
  units: kelvin

melting_temperature_ci:
  type: Number
  description: 95% confidence interval in melting temperature prediction
  units: kelvin

LAMMPS_log:
  type: Text
  description: Name of the log file written by LAMMPS

time_series:
  type: Array
  description: Instantaneous time series
  units: picosecond

temperature_series:
  description: Instantaneous temperature during the simulation
  type: Array
  units: kelvin

potential_energy_series:
  type: Array
  description: Instantaneous potential energy during the simulation
  units: electron_volt

volume_series:
  type: Array
  description: Instantaneous volume during the simulation
  units: angstrom ** 3
```



Parameterize a Sim2L

Setting SimTool Inputs

Now we will setup the inputs and run a first simulation. Important aspects on SimTool inputs are:

- Inputs are validated
- Unit conversion is done automatically so the SimTools always gets the right number - the simtool library uses
- Note the input variable type element - the SimTool wants to get atomic mass in amu, but the user can set the

```
In [5]: # range checking
inputs.Tsolid.value = '50000 C'

-----
ValueError                                Traceback (most recent call last)
<ipython-input-5-8937c10a7204> in <module>
      1 # range checking
----> 2 inputs.Tsolid.value = '50000 C'

/appshare64/debian7/anaconda/anaconda-6/lib/python3.7/site-packages/simtool/params
  491         raise ValueError("Minimum value is %g" % self.min)
  492         if self.max is not None and newval > self.max:
--> 493         raise ValueError("Maximum value is %g" % self.max)
  494         self._value = newval
  495

ValueError: Maximum value is 5000

In [6]: # unit conversion
inputs.Tsolid.value = '1000 C'
inputs.Tsolid.value

Out[6]: 1273.15

In [7]: inputs.Tsolid.value

Out[7]: 1273.15

In [8]: # Element type conversion. The SimTool needs atomic mass.
inputs.mass.value = 'Al'
inputs.mass.value

Out[8]: 26.9815385
```

4. Parameterize input object

- Unit conversion with pint
- Element type with mendeleev



Run a Sim2L & view results

Run the SimTool

```
In [9]: inputs.Tsolid.value = 800  
inputs.Tliquid.value = 2500
```

```
In [*]: r = Run(MeltKIM, inputs)
```

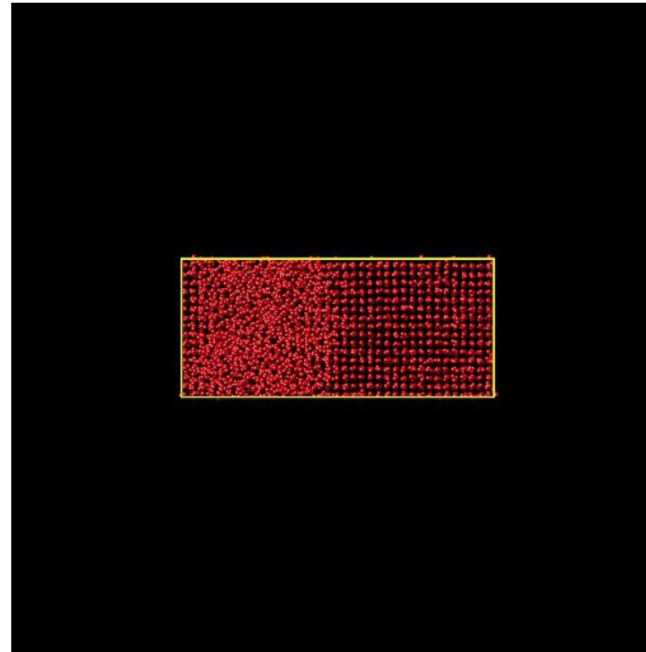
```
submit --local /apps/bin/ionhelperGetSimToolResult.sh meltingkim r31  
RUNS/09456b2cc6314d3293dcf85e021111c5/inputs.yaml  
submit --local /apps/bin/ionhelperRunSimTool.sh meltingkim r31  
RUNS/09456b2cc6314d3293dcf85e021111c5/inputs.yaml
```

```
Input Notebook: /apps/meltingkim/r31/simtool/meltingkim.ipynb  
Output Notebook: meltingkim.ipynb  
Executing: 53%|????? | 18/34 [00:20<00:03, 4.01cell/s]
```

5. Run the Sim2L

```
In [12]: # Let's look at the final configuration first - to determine whether we have liquid and solid in equilibrium  
r.read('final_snapshot')
```

Out[12]:



Final snapshot

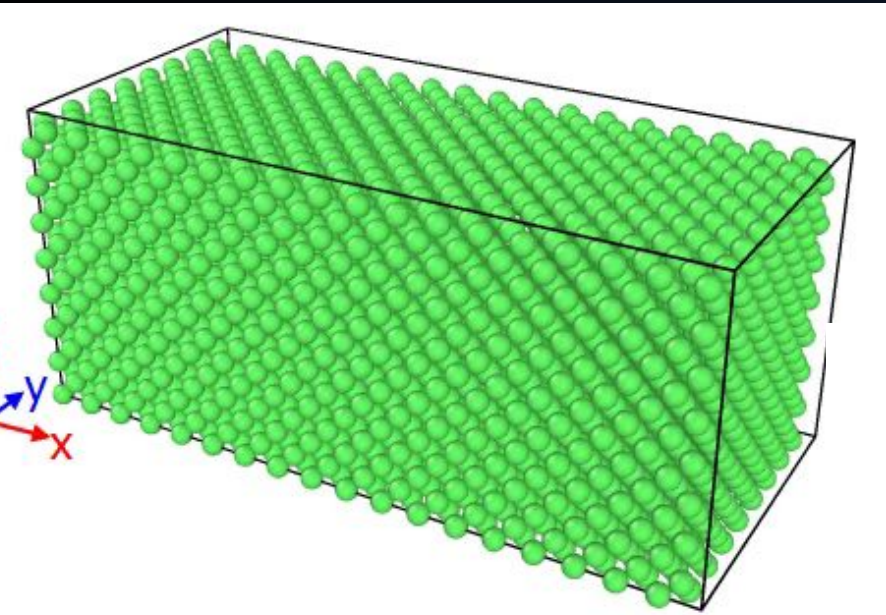
6. Explore results

Predicted values

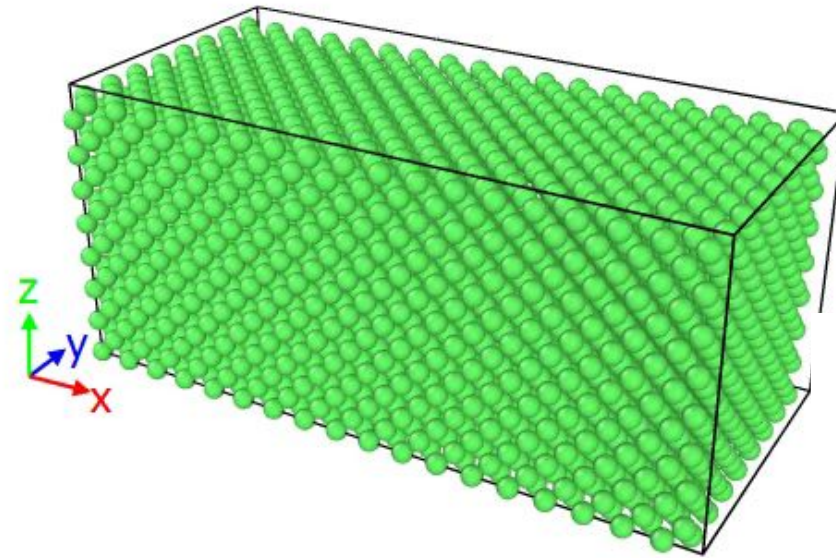
```
In [13]: print ("Predicted melting temperature for this potential: ", (r.read('melting_temperature')))  
print ("95% confidence interval: ", (r.read('melting_temperature_ci')))  
print ("Fraction of system solid: ", (r.read('fraction_solid')))  
print ("Fraction of system liquid: ", (r.read('fraction_liquid')))
```

```
Predicted melting temperature for this potential: 1708.2981214876029  
95% confidence interval: 3.018529352353528  
Fraction of system solid: 0.4926215277777778  
Fraction of system liquid: 0.49609375
```

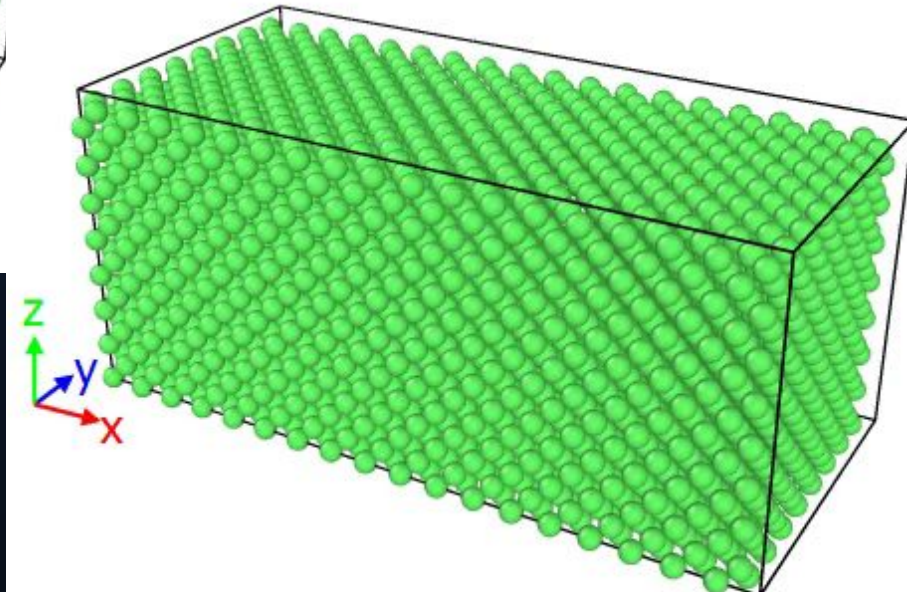
Sim2L in action: melting temperature



Too cold

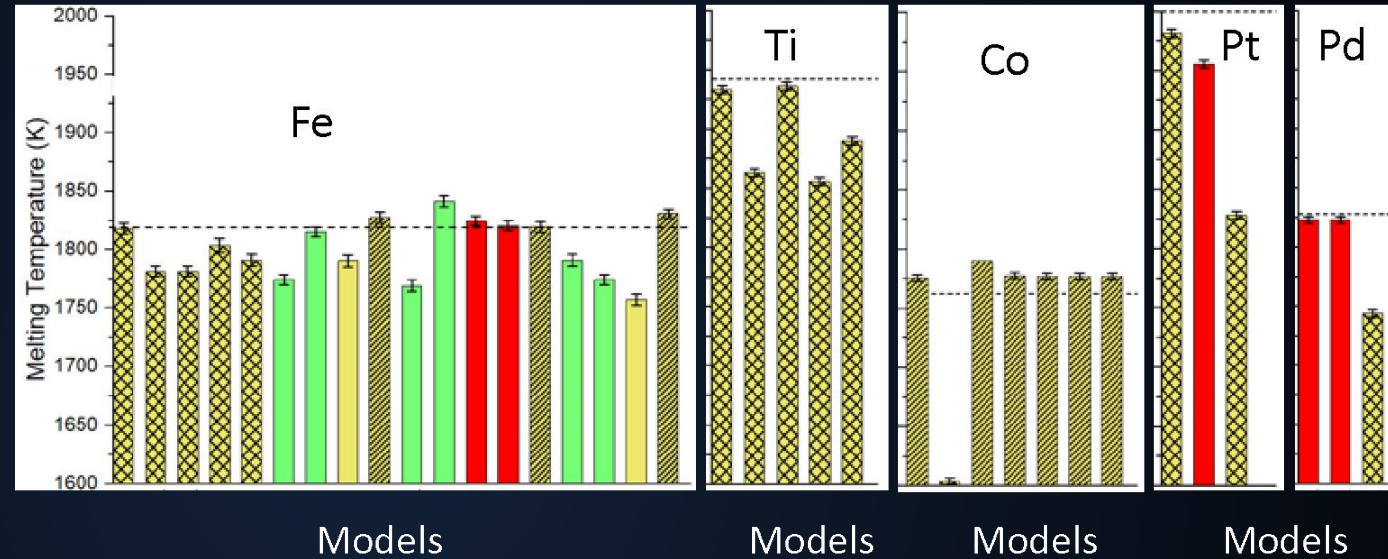


Goldilocks region
(melting temperature)

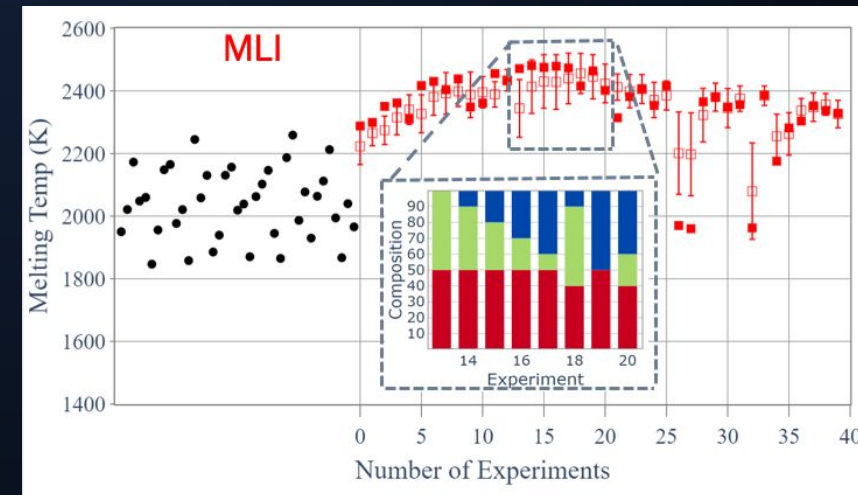


Cool things you can do with a Sim2L

High throughput simulations:



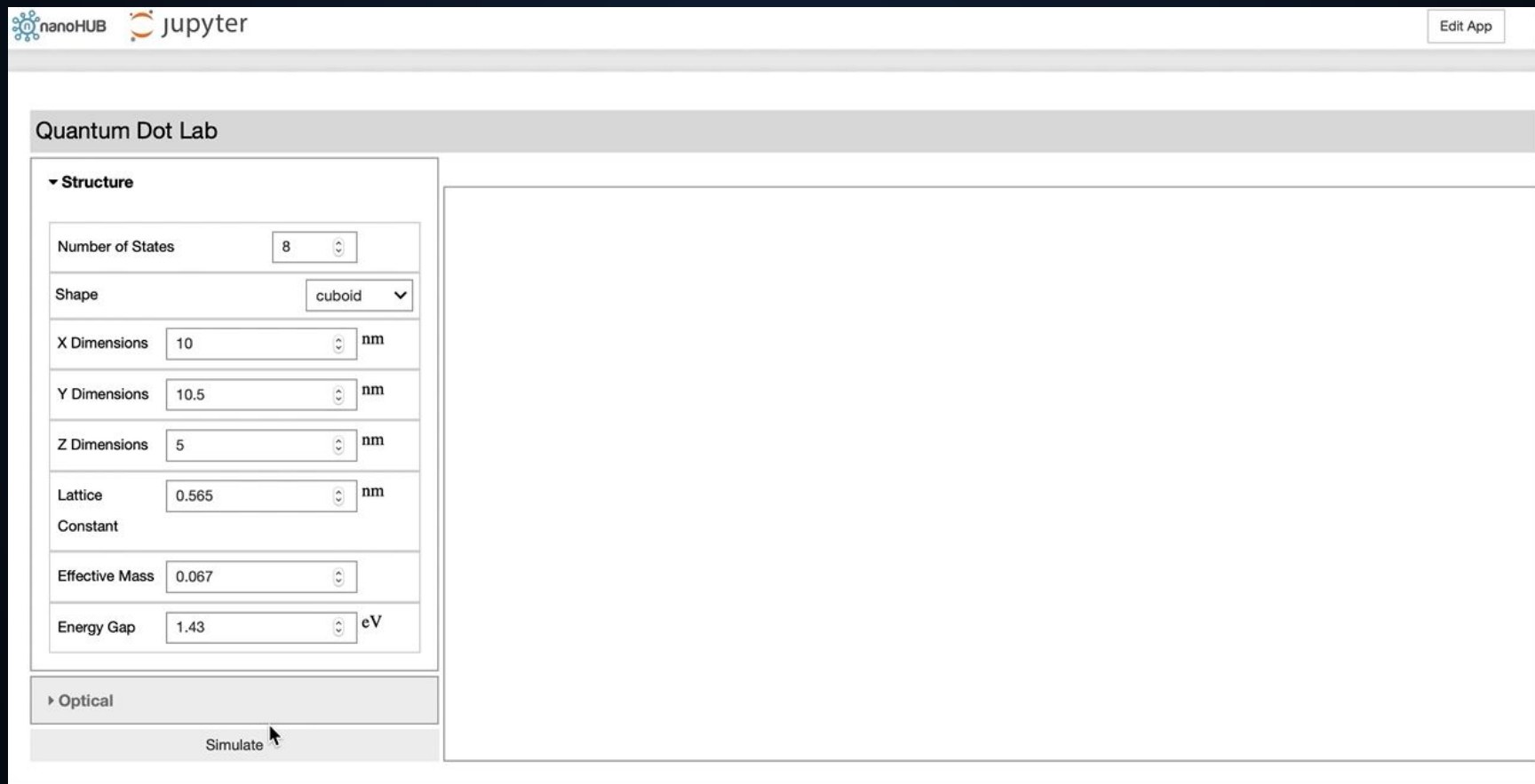
Machine learning driven workflows:



Cool things you can do with a Sim2L: II

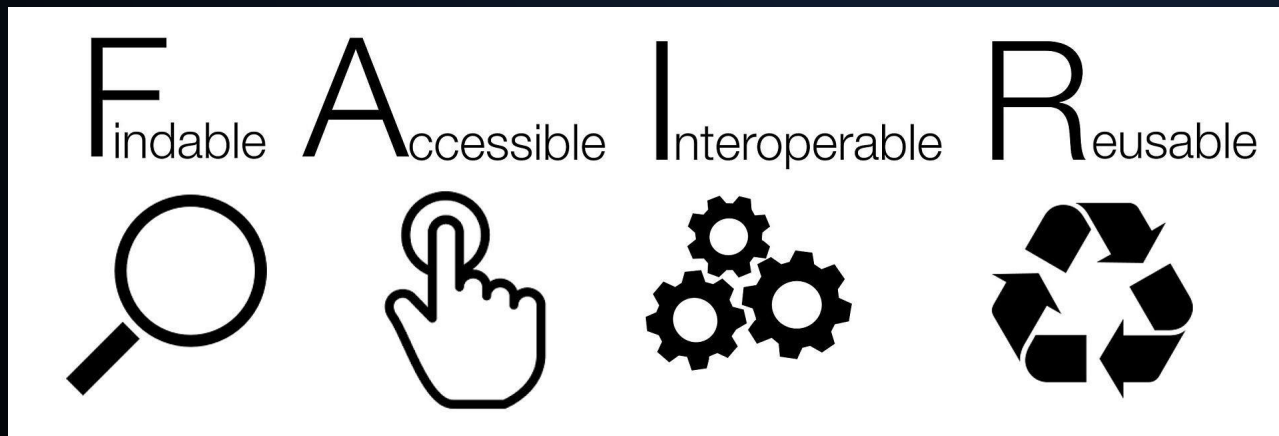
Apps designed for end users

- Researchers and instructors
- Focus on the physics and not on the computational details



Summary – Sim2L features

- End to end computational workflow (Repro)
- Published Sim2Ls:
 - Are containerized (Repro)
 - Have DOIs and are indexed by Web of Science & google scholar (F,A)
- Declared and validated inputs and outputs (R, I)
- Services, including metadata, are queryable (F, A, I)
- Automatic result caching (A, R, I)



+ **Repro**ducible

Additional resources

- Sim2L Documentation
 - <https://simtool.readthedocs.io/en/latest/>
- Explore a Sim2L example including all possible IN/OUT types
 - <https://nanohub.org/tools/introtosimtools/>
- Learn about nanoHUB software development environment
 - Overview of possible app/tool types & publication process:
 - <https://nanohub.org/whypublish>
 - Working with Jupyter in nanoHUB:
 - <https://nanohub.org/resources/34611>

Thanks

