Big Integer Operations with Dask

Specific Application

Problem to solve: Library for abstract algebra operations (e.g. matrix multiplication, addition) on VERY big integers (up to 2^10000) with python

Type of Work:

- Partitioning lists/arrays of large integers
- Data parallel work
- Reducing lists in uncommon ways

Other uses for big integers:

- Cosmology
- Hash tables
- Random numbers/probability simulations
- Exact precision
- Exploring large math sequences

Dask...

- Makes the program scalable for a large range of computers
- Makes already complicated abstract algebra easier to understand, prototype, and modify
- Can be “hidden” from user of larger applications/libraries
- Complex sequence of operations dealt with well by Dask task graph abilities

Architectures

- Summit Supercomputer
  - Per Node:
    - Two 22-core IBM POWER9 processors (4 threads per core)
    - Six NVIDIA Volta V100 accelerators
  - Tested on one, two, four nodes
- Raptor
  - Single node of Summit
  - Unrestricted by permissions and security firewalls
  - Tops out at 24 threads

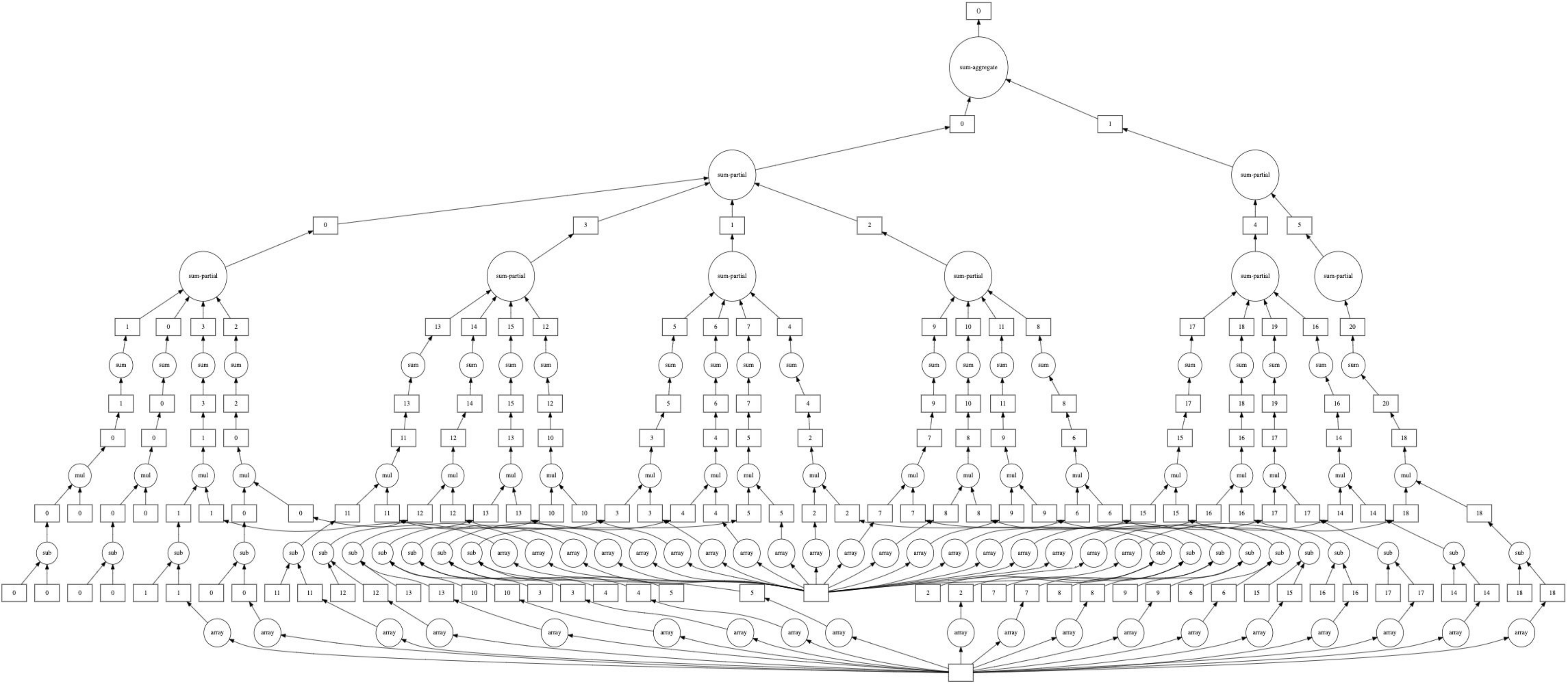
Experiences with Dask Primitives

- Delayed
  - Good for work that has to be ‘computed’/seen often
  - Good for unique/fine-tuned operations
  - Large overhead when the data is big and must be “delayed twice”
  - You can’t “chunk” lists of delayed objects
  - Occasionally confuses scheduler if wrapped around outside library objects
- Bags
  - Good for preprocessing
  - Good at holding python objects (even different types)
  - Doing “custom” mappings and reductions
  - Do not preserve order, cannot be called by index

Experiences with Dask Primitives

- Arrays
  - Good for performing simple operations in parallel, comparative usability to parallel for loops
  - Figuring out best chunking and distribution takes some testing
  - Do not hold python objects (i.e. ints that don’t fit into int64) well
  - Combining/zipping arrays is limited to the blockwise() method, limited reduction ability, methods like random do not work for large numbers
- Compute/persist
  - Combined with automatic task graphs, provides excellent barrier method and ability to order and track operations

Efficient Task Graph

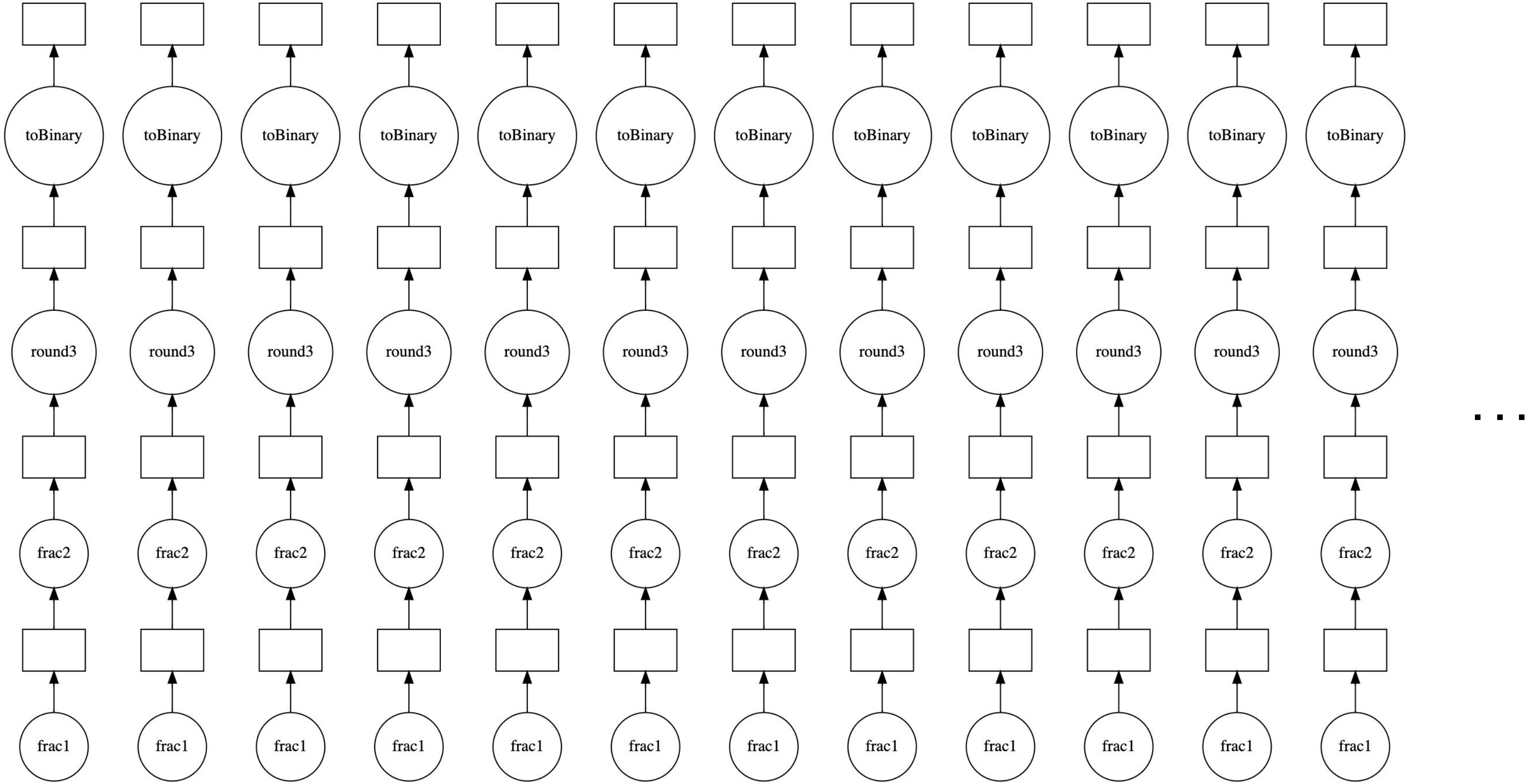


Dask Array Parallelization

Algorithm: calculation of deltas, then array multiplications, then large sum

```
b0 = [delayed(self.rgen.random_element)(-2**self.alpha,2**self.alpha) for i in range(self.tau)]
bi0= [delayed(self.rgen.random_element)(-2**self.alphai,2**self.alphai) for i in range(self.l)]

b1 = dask.compute(*b0)
bi1 = dask.compute(*bi0)

b = da.from_array(b1, chunks=self.chunks)
bi = da.from_array(bi1, chunks=self.chunks)

x = da.blockwise(operator.sub, 'i', (da.from_array(self.rgen.make_pri(self.x0,self.tau,self.x_seed), \
  chunks=self.chunks)), 'i', self.x_deltas, 'i', dtype=object)
xi = da.blockwise(operator.sub, 'i', (da.from_array(self.rgen.make_pri(self.x0,self.l,self.xi_seed), \
  chunks=self.chunks)), 'i', self.xi_deltas, 'i', dtype=object)
ii = da.blockwise(operator.sub, 'i', (da.from_array(self.rgen.make_pri(self.x0,self.l,self.ii_seed), \
  chunks=self.chunks)), 'i', self.ii_deltas, 'i', dtype=object)

m_xi = da.blockwise(operator.mul, 'i', (da.from_array(m, chunks=self.chunks)), 'i', xi, 'i', dtype=object)
bi_ii = da.blockwise(operator.mul, 'i', bi, 'i', ii, 'i', dtype=object)
b_x = da.blockwise(operator.mul, 'i', b, 'i', x, 'i', dtype=object)

big = da.sum(da.concatenate([m_xi, bi_ii, b_x]))

final = modNear(big.compute(),self.x0)
```

Efficient Task Graph



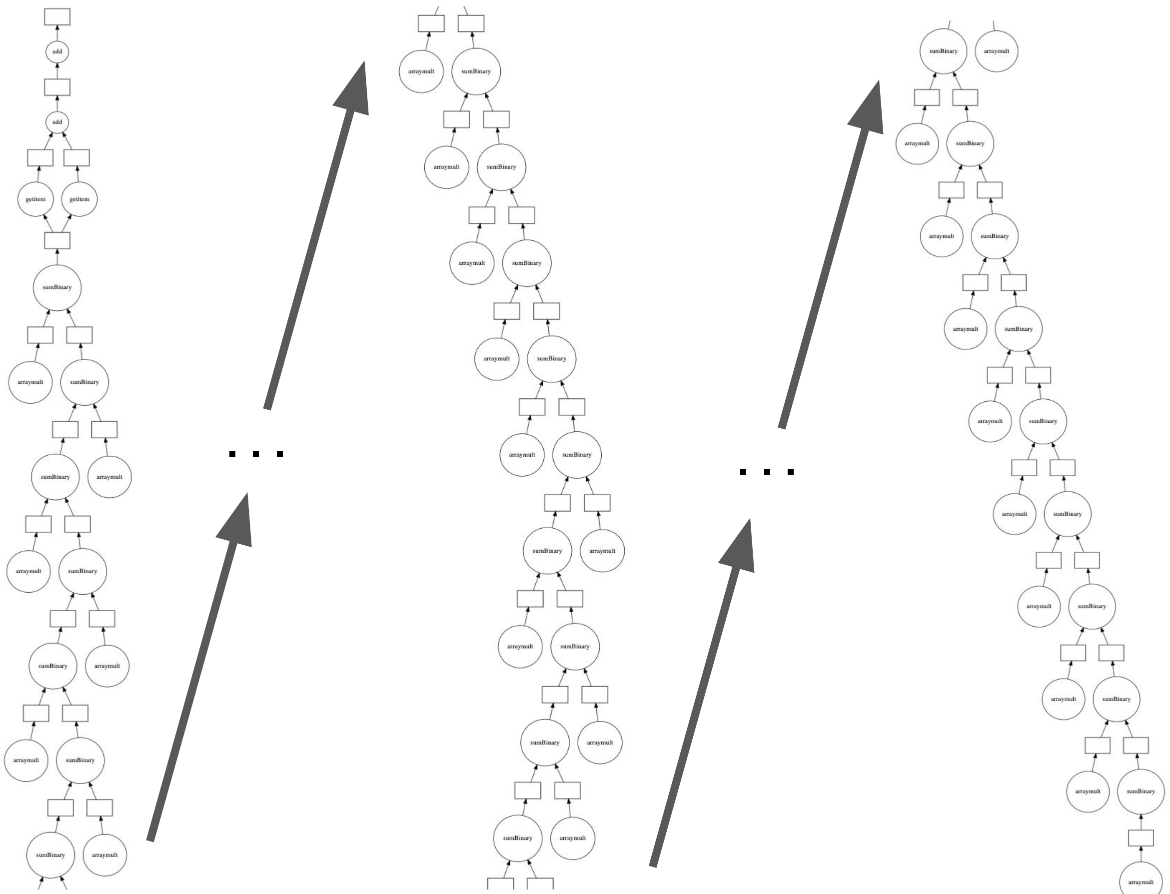
Dask Delayed Parallelization

Algorithm: rounding and truncation of large rational number into binary array representation, part of a “noise reduction” process of larger matrix multiplication

```
#"expand"
y = [frac1(ui,self.kap,c) for ui in u]
z = [frac2(yi) for yi in y]
z1 = [round3(zi) for zi in z]
zbin = [toBinary(zi,self.n+1) for zi in z1]

z_comp = dask.compute(*zbin)
```

```
@dask.delayed
def frac1(u,k,c):
  return mpq(u,2**k)*c

@dask.delayed
def frac2(y):
  return mpz((y%2)*32)

@dask.delayed
def round3(z):
  return c_div(z,mpz(2))

@dask.delayed
def toBinary(x,l):
  if (x==32): return np.array([0]*l)
  return np.array(digits(x+2**l)[:-1])

def digits(x):
  le = list('{0:0b}'.format(x))
  le.reverse()
  return le
```

"Inefficient" Task Graph



Compensating with Dask Delayed

```
li = [arraymult(ski,cei) for ski,cei in zip(o_comp,z_comp)]

Q_adds = [0 for i in range(self.n+1)]

for t in range(self.Theta):
  Q_adds = sumBinary(Q_adds,li[t])

rounded = Q_adds[-1] + Q_adds[-2] #"round"

final = rounded + (c & 1)

return final.compute()
```

```
@dask.delayed
def sumBinary(a,b):
  c=[a[0]+b[0]]
  carry=a[0]*b[0]

  for i in range(1,len(a)-1):
    carry2=(a[i]+b[i])*carry+a[i]*b[i]
    c.append(a[i]+b[i]+carry)
    carry=carry2

  c.append(a[-1]+b[-1]+carry)
  return c

@dask.delayed
def arraymult(c,a):
  return [c*int(xi) for xi in a]
```

Algorithm: summation of many binary representations in a “schoolbook” method, with carries, etc; part of the “noise reduction” process of larger matrix multiplication

Experiences with Dask Scheduling

- Single Machine Schedulers
  - Easy to get running anywhere (except, apparently, Summit)
  - Multiple options (threads, debugging option, etc)
  - Limited use
- Distributed Scheduler
  - Great speed-ups from vanilla python
  - Much more complicated to get running, Summit limits certain functionalities (job queue, etc.)
  - Errors are hard to debug: things that work fine on single machine schedulers sometimes malfunction due to strange package dependencies, unreplicatable network/worker errors, etc.
- Different schedulers can be used for different parts of the code, if you have a computer that runs both
- Dashboard will not run from Summit (port blocked)

Dask Primitive Wishlist

- Fine tuning of Array.reduction method
- Expanded object handling for Arrays

or

- Ordered Bags
- Ability to ask for specific indices from bags

or

- Data Structure between those two things
- Better python object representation and operations

	Python/Dask	C++/OpenMP	Julia
Overall Performance	~10x slower than C++	Excellent	Surprisingly comparable to C++
Speedup/Scalability	Good speed up from vanilla python, though some operations do better than others	Requires a lot of fine work, but there ends up being much less overhead; scales the best	Good for less work; somewhat unpredictable due to garbage collector
Programmability	Everyone (inside and outside CS) basically already knows it	More complicated for non-CS people; invisible memory errors/race conditions easier to miss	Straightforward, much like Python; parallel programming is “built in”; but newish language
Portability	Simple conversion between sequential, single machine parallelism, and distributed machine parallelism	Requires MPI for distribution, otherwise easy conversion between sequential and parallel	Requires code changes and MPI (for now) for distributed memory on Summit; installation challenges
Runs on Summit	Mostly	Yes	Mostly

Benchmarks for specific multiplication operation