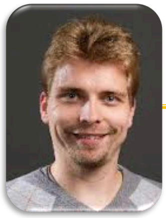

UC Berkeley EECS
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Computational Structures in Data Science

Lecture #13: Performance, Distributed Computing, Summary

千人狂歡　最受歡迎的程式課

http://www.cw.com.tw/article/article.action?id=5079340

December 2nd, 2016 http://inst.eecs.berkeley.edu/~cs88

Administrivia

- This is the last lecture. Next week: Q&A for finals.
- Today: HKN review!
  Please do the survey and give us good grades! ☺
- Thank you:
  - TAs!
  - Lab Assistants!
  - UC Berkeley Staff!

Computational Concepts Toolbox

- Data type: values, literals, operations,
- Expressions, Call expression
- Variables
- Assignment Statement
- Sequences: tuple, list
- Dictionaries
- Data structures
- Tuple assignment
- Function Definition Statement
- Conditional Statement
- Iteration: list comp, for, while
- Lambda function expr.
- Higher Order Functions
  - as Values, Args, Results
- Higher order function patterns
  - Map, Filter, Reduce
  - Function factories
- Recursion
  - Linear, Tail, Tree
- Abstract Data Types
- Mutation
- Iterators and Generators
- Object Oriented Programming, Classes
- Exceptions
- Declarative Programming
- Distributed Computing

Recap: Complexity

- Example: Matrix Multiply
  - How many Multiplies? Adds? Ops? How much time ?
  - As a function of n ?

```
for i in 0 to n-1:
    for j in 0 to n-1:
        C[i][j] = 0
        for k in 0 to n-1:
            C[i][j] = C[i][j] + A[i][k]*B[k][j]
```

We say it is O(n^3) "big-O of n^3" as an *asymptotic upper bound*

time(n) < c • n^3, for some suitably large constant c for any instance of the inputs of size n.

A more subtle complexity example

- **What is the "complexity" of finding the average number of factors of numbers up to n?**

```
def factors(n):
  return [x for x in range(2, max(n, ceil(sqrt(n))))
                                       if n % x == 0]
def ave_factor(n):
    all_factors = map(factors, range(n))
    all_lens = map(len, all_factors)
    return sum(all_lens)/n
```

$n^{1/2}$

n

```
from timeit import default_timer as timer

def timeit(fun):
    """ Rtn timer for fun(i) in secs. """
    def timer_fun(i):
        start = timer()
        fun(i)
        end = timer()
        return (end-start)
    return timer_fun
```

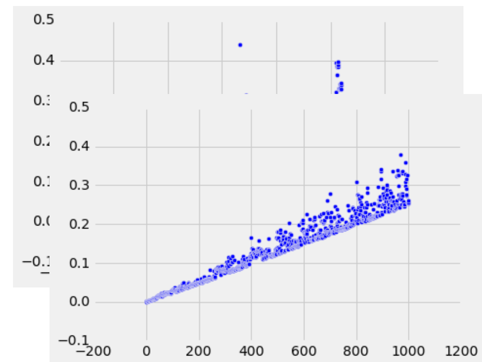

How long does factors take?

In [9]:
```
tbl = Table().with_column('n', np.arange(0,1000, 1))
tbl['factors'] = tbl.apply(factors, 'n')
tbl['n_factors'] = tbl.apply(len, 'factors')
tbl['secs'] = tbl.apply(timeit(factors), 'n')
tbl
```

Out[9]:

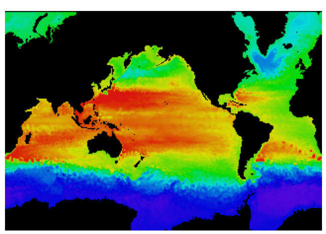
n	factors	n_factors	secs
0	[]	0	9.76503e-06
1	[]	0	2.40898e-06
2	[]	0	1.34797e-06
3	[]	0	3.49898e-06
4	[2]	1	2.74903e-06
5	[]	0	2.43704e-06
6	[2, 3]	2	3.019e-06
7	[]	0	2.78e-06
8	[2, 4]	2	3.28396e-06
9	[3]	1	3.74601e-06

... (990 rows omitted)



Big Data, Big Problems

- **Performance terminology**
  - **the FLOP: <u>FL</u>oating point <u>OP</u>eration**
  - **"flops" = # FLOP/second is the standard metric for computing power**
- **Example: Global Climate Modeling**
  - **Divide the world into a grid (e.g. 10 km spacing)**
  - **Solve fluid dynamics equations for each point & minute**
    - » **Requires about 100 Flops per grid point per minute**
  - **Weather Prediction (7 days in 24 hours):**
    - » **56 Gflops**
  - **Climate Prediction (50 years in 30 days):**
    - » **4.8 Tflops**
- **Perspective**
  - **Intel Core i7 980 XE Desktop Processor**
    - » **~100 Gflops**
    - » **Climate Prediction would take ~5 years**



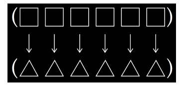
www.epm.ornl.gov/chammp/chammp.html

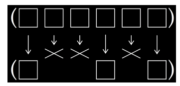
What Can We Do? Use Many CPUs!

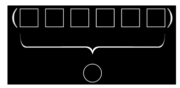
- **Supercomputing** – like those listed in top500.org
  - Multiple processors "all in one box / room" from one vendor that often communicate through shared memory
  - This is often where you find exotic architectures
- **Distributed computing**
  - Many separate computers (each with independent CPU, RAM, HD, NIC) that communicate through a network
    - » <u>Grids</u> (heterogenous computers across Internet)
    - » <u>Clusters</u> (mostly homogeneous computers all in one room)
      - Google uses commodity computers to exploit "knee in curve" price/performance sweet spot
  - It's about being able to solve "big" problems, not "small" problems faster
    - » These problems can be <u>data</u> (mostly) or <u>CPU</u> intensive

Recap: Filter, Map, Reduce

- Functions as Data
- Higher-Order Functions
- Useful HOFs (you can build your own!)
  - map function over `list`
    - » Report a new list, every element `e` of `list` becoming `function(e)`
  - filter items such that `predicate` from `list`
    - » Create a new list, keeping only elements `e` of `list` if `predicate(e)`
  - reduce with `function` over `list`
    - » Combine all the elements of `list` with `function(e)`







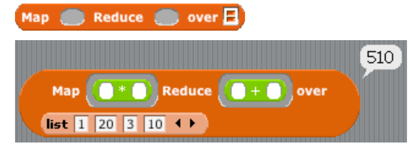
- Example:

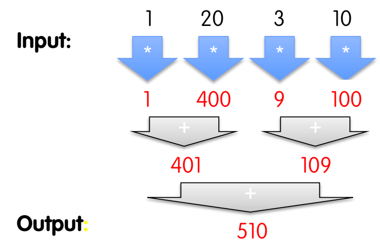
  filter ➔ map ➔ reduce

en.wikipedia.org/wiki/MapReduce

Google's MapReduce Simplified

- Filter: Chunk data and send to different CPUs.
- Map: Apply function to data chunks on different CPUs.
- Reduce: Combine results from different CPUs.
  - Reducer should be associative and commutative
- Imagine 10,000 machines ready to help you compute anything you could cast as a MapReduce problem!
  - This is the abstraction Google is famous for authoring
  - The system takes care of load balancing, dead machines, etc.



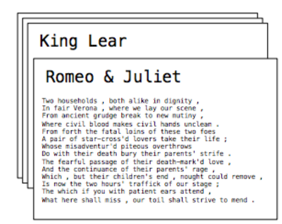


MapReduce: Advantages/Disadvantages

- Now it's easy to program for many CPUs
  - Communication management effectively gone
  - Fault tolerance, monitoring
    - » machine failures, suddenly-slow machines, etc are handled
  - Can be much easier to design and program!
  - Can cascade several (many?) MapReduce tasks
- But… it might restrict solvable problems
  - Might be hard to express problem in MapReduce
  - Data parallelism is key
    - » Need to be able to break up a problem by data chunks

Apache Spark (from Berkeley)

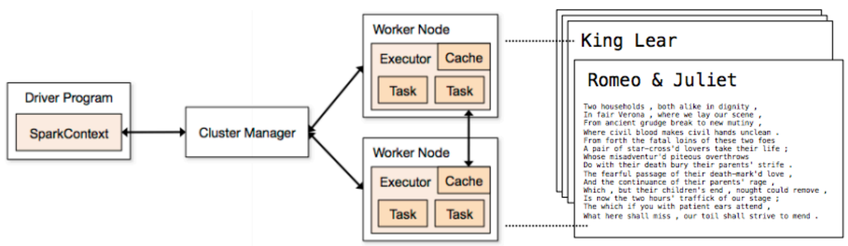
- Data processing system that provides a simple interface to analytics on large data
- A Resilient Distributed Dataset (RDD) is a collection of values or key-value pairs
- Support the operations you are familiar with
  - Data-Parallel: map, filter, reduce
  - Database: join, union, intersect
  - OS: sort, distinct, count
- All of can be performed on RDDs that are partitioned across machines



Spark Execution Model

Processing is defined centrally and executed remotely

- **A RDD is distributed over workers**
- **A driver program defines transformations and actions on RDDs**
- **A cluster manager assigns task to workers**
- **Workers perform computation, store data, & communicate with each other**
- **Final results communicate back to driver**

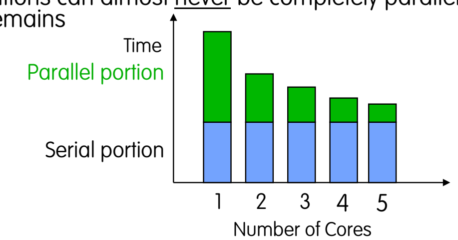


Distributed Computing Challenges

- **Communication is fundamental difficulty**
  - **Distributing data, updating shared resource, communicating results, handling failures**
  - **Machines have separate memories, so need network**
  - **Introduces inefficiencies: overhead, waiting, etc.**
- **Need to parallelize algorithms, data structures**
  - **Must look at problems from parallel standpoint**
  - **Best for problems whose compute times >> overhead**

Speedup Issues: Amdahl's Law

- Applications can almost never be completely parallelized; some serial code remains



- s is serial fraction of program, P is # of cores (was processors)
- **Amdahl's law:**

Speedup(P) = Time(1) / Time(P)

≤ 1 / (s + [(1-s) / P)], and as P → ∞

≤ 1 / s

Amdahl's Law: Conclusion

- **Computer Science View**: Even if the parallel portion of your application speeds up perfectly, your performance will be limited by the sequential portion. ☹
- **Data Science View:** Often, as the data gets large, the work that can be parallelized grows faster than the size of the data. ☺

Fundamental Change in Perspective!

Summary: Data science

https://www.youtube.com/watch?v=TzxmjbL-i4Y

Summary: CS88 a journey!

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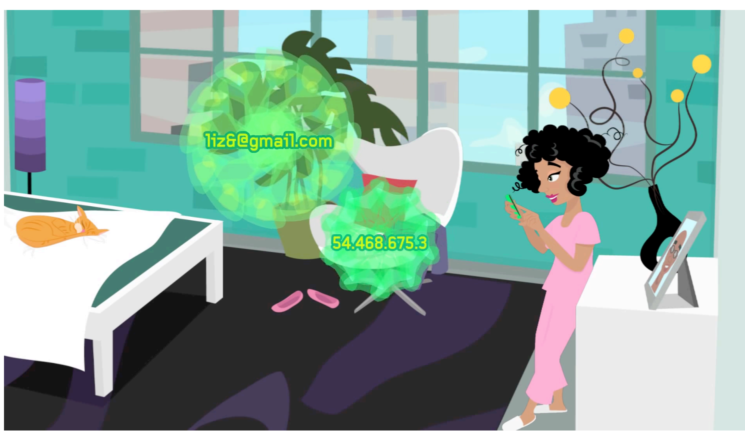
Final thought: A note of caution



https://www.youtube.com/watch?v=bqWuioPHhz0

CS88: Final slide

Thank you so much!