MapReduce programming

DAT470/DIT065 Computational techniques for large-scale data

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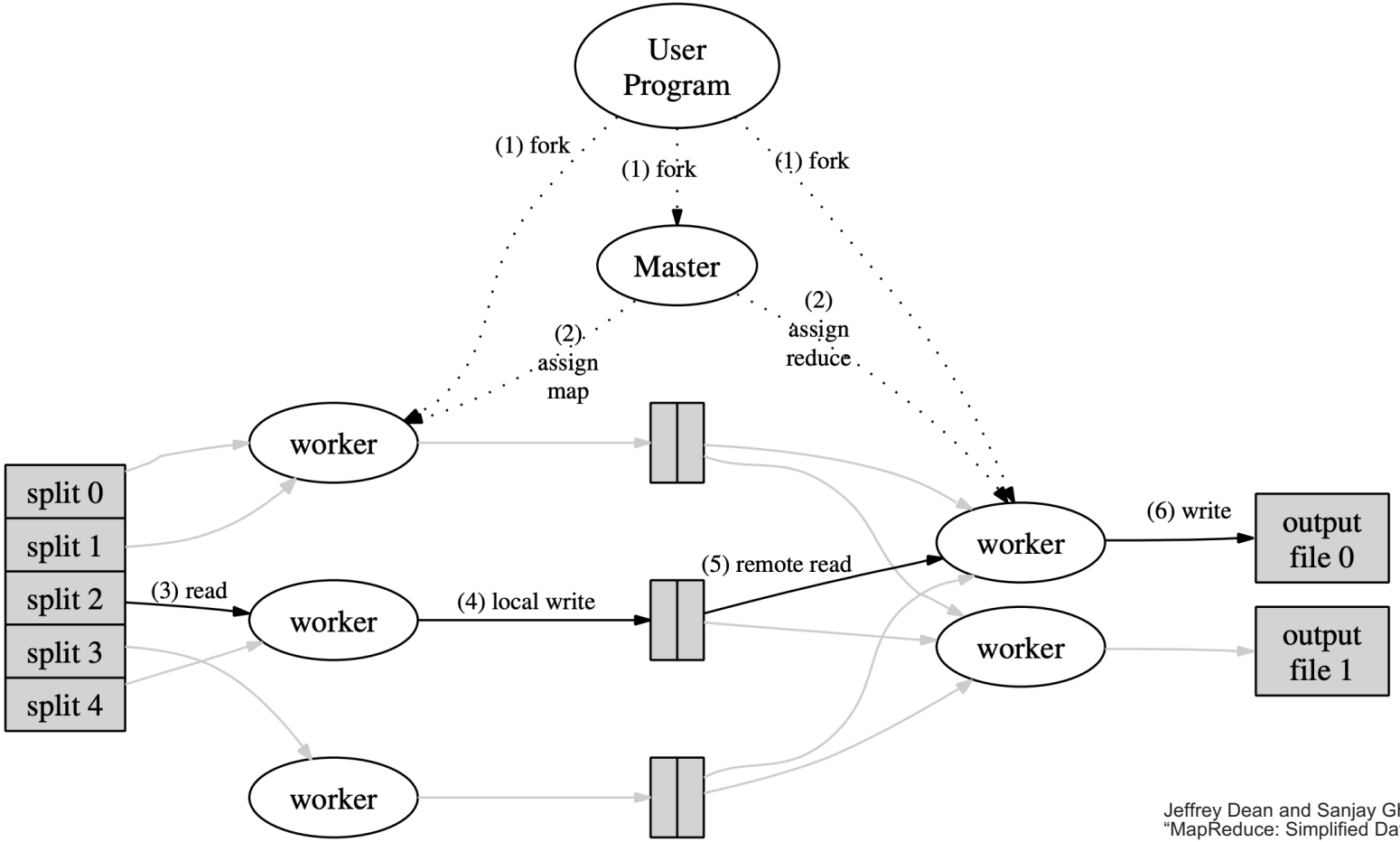
Motivation

- Computing on a large number of computers has challenges
  - Data has to be stored in a distributed fashion: no individual node can hold all data
  - Computing is **error-prone**: computers fail
  - **I/O bottleneck** presents a challenge: moving data from one compute node to another is very expensive
  - Coordinating computation is very difficult and laborious
- **MapReduce** is a solution that attempts to solve these some of these problems by assuming a (somewhat rigid) model of computation
  - Computation is **brought to data**: reduces the amount of I/O
  - Computation is modelled operations that adhere to a strict pattern, so they are easy to schedule
  - Likewise, if we detect a fault, we can simply replay those operations that failed

Map & Reduce

- In MapReduce programming, all data is treated as **key-value** pairs
- Computations are composed of two kinds of operations: **map** and **reduce** operations
- Map: $(K_1, V_1) \rightarrow \text{List}((K_2, V_2))$
  - Each key-value pair is mapped to a one or more key-value pairs
  - Maps are executed in parallel on different nodes (wherever the data lies)
  - Cf. Python's `map`
- After the map, the data is **shuffled** by hashing the keys
  - This (pseudorandomly) distributes the output to different nodes
  - Each key-value pair sharing the same key is guaranteed to end on the same node
- Reduce: $(K_2, \text{List}(V_2)) \rightarrow \text{List}((K_3, V_3))$
  - All values that were mapped to the same key are given as a list
  - **Typically**, reduce would then compute a single value from that, but can in practice return multiple key-value pairs
  - The function should be **commmutative** and **associative** because the order of values cannot be guaranteed
  - Cf. Python's `reduce`



Jeffrey Dean and Sanjay Ghemawat: "MapReduce: Simplified Data Processing on Large Clusters" (2004)

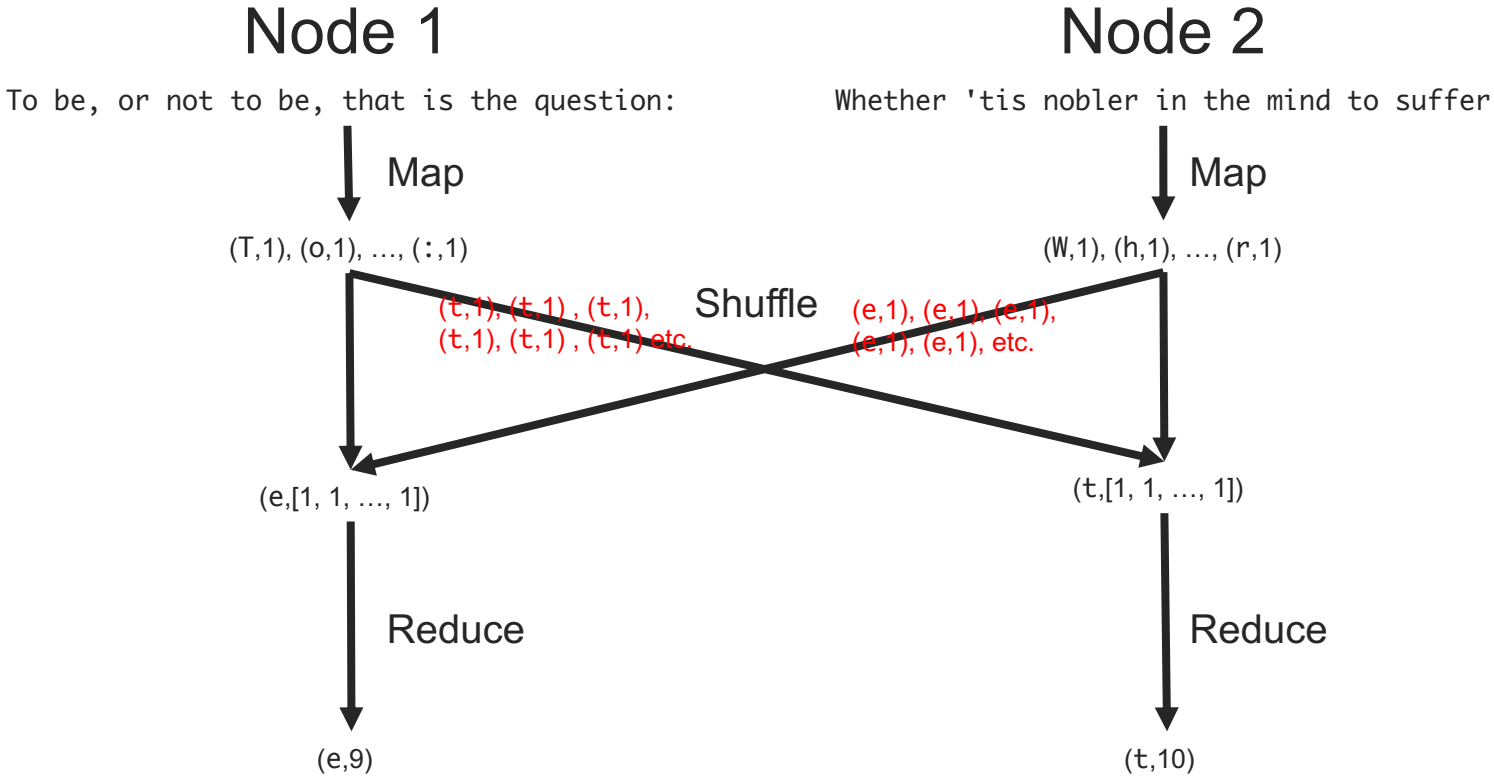
Example

- Let us count the frequency of each letter as in the previous lecture
- Data will be split by the lines; the input key is not significant (it can be a dummy key or line number or something of the sort)
- Map:
  - Key: *ignored*, value: line of text
  - For each character c in the line, emit (c,1)
  - "We saw c once"
- Data will be shuffled to different nodes; all 1s of the same character will end up on the same node
- Reduce:
  - Key: c, value: list $v_1, v_2, \ldots$ of 1s, corresponding to the count
  - Emit (c, $\sum v_i$)

Execution example

- Suppose node 1 holds the line `To be, or not to be, that is the question:` and node 2 holds the line `Whether 'tis nobler in the mind to suffer`
- The **mapper** of node 1 emits (T,1), (o,1), …, (:,1)
- The mapper of node 2 emits (W,1), (h,1), …, (r,1)
- Data is then shuffled
  - Suppose e ends up on node 1 and t on node 2
  - Five pairs (e,1) are communicated from node 2 to node 1
  - Six pairs (t,1) are communicated from node 1 to node 2
- For the key e, the reducer on node 1 takes in (e,[1,1,…,]), a list of 9 ones
- Reducer on node 1 emits (e,9)
- For the key t, the reducer on node 2 takes in (t,[1,1,…,]), a list of 10 ones
- Reducer on node 2 emits (t,10)

Execution example



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- **Apache Hadoop** is a free software ecosystem for big data processing
- Hadoop MapReduce is the standard implementation of MapReduce (originally introduced by Google)
- The ecosystem contains other supporting components, such as Hadoop Distributed Filesystem (HDFS), a fault-tolerant distributed filesystem that we'll discuss on the next lecture

MRJob

- MRJob is a Python library for implementing MapReduce jobs
- Works like this: the user implements a subclass of job class and implements the required operations
- Jobs can be run locally (with the “local runner”, this is the approach we’ll adopt in our assignments), or through the Hadoop infrastructure
- Specialty: The Python file implementing the class **must not contain** anything else
  - This is because the job is sent to Hadoop for running and this sets limitations on, e.g., how the Python code may interact with its environment

Generator functions

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- The functions in MRJob are written as **generator functions**
- These functions are syntactic sugar for implementing **lazy functions** that behave as if **iterators**
- In Python, an object is **iterable** if it implements `__iter__` and `__next__`, that is, it allows one to create an **iterator** and (typically) go through the data structure one element at a time by advancing the iterator
  - All basic data structures in the Python standard library are iterable
- The functions `__iter__` and `__next__` are usually called via the convenience functions `iter` and `next`, respectively
  - Suppose `X` is some kind of collection
  - `it = iter(X)` returns an iterator to the collection
  - `next(it)` returns the next element in the collection and advances the iterator; if all elements have been returned, it raises the `StopIteration` exception instead
- The Python for `x in X` loop is essentially syntactic sugar for the following construct:
  - Create an iterator with `it = iter(X)`
  - Get the next element with `x = next(it)`
  - Catch the `StopIteration` exception and break from loop

Example

- These two are functionally the same

```
for x in X:
    print(x)
```

```
it = iter(X)
while True:
    try:
        x = next(it)
        print(x)
    except StopIteration:
        break
```

Generator functions

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- If a Python function contains a `yield` keyword, it is implicitly wrapped into an iterator object!
  - The next value returned by `__next__` is determined by `yield`
  - When the function ends executing, it raises `StopIteration`
  - This means that we can say `x in f()`
- Advantages:
  - From the caller's point of view, the function behaves like a collection even though the values do not exist at the moment of call
  - This enables us to lazily construct the values that the caller wants only upon need
  - This can save **a lot of** space and time if we do not need access to all values at one time, or if we abort early
- Disadvantages:
  - This introduces tacitly new stateful objects which we need to be aware of
  - This can be inefficient if used inconsiderately

Example: return the *n* first Fibonacci numbers

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```
def fibonacci(n):
    x = 0
    y = 0
    z = 1
    for _ in range(n):
        x = y
        y = z
        z = x+y
        yield y

if __name__ == '__main__':
    for x in fibonacci(10):
        print(x)
```

Example: Letter count with MRJob

```
from mrjob.job import MRJob

class MRLettercount(MRJob):
    def mapper(self, _, line):
        for c in line:
            yield (c,1)

    def reducer(self, c, ones):
        yield (c,sum(ones))

if __name__ == '__main__':
    MRLettercount.run()
```

This class defines a MapReduce job; we extend it

The map function is defined by overriding the `mapper` function

We ignore the key

Values are returned lazily; the function is actually a generator

The reducer works just the same

The default runner reads data from a file or stdin and provides standard command-line arguments; there must be **nothing** else in the .py file

Example: Letter count with MRJob

```
(mrjob) karppa@CM-DWQ77WNX67 lecture6 % cat lines.txt | tee /dev/tty | python3 mrjob_lettercount1.py
-r local --num-cores 4 2> /dev/null
To be, or not to be, that is the question:
Whether 'tis nobler in the mind to suffer
"q"     1
"r"     4
"s"     4
"t"     10
"e"     9
"f"     2
"h"     5
"i"     5
"l"     1
"m"     1
"n"     5
"o"     7
"'"     1
","     2
":"     1
"T"     1
"W"     1
"a"     1
"b"     3
"d"     1
"u"     2
" "     16
```

Protip: print the intermediate status on screen by writing to the terminal file

Use “local” runner (default is debug runner which does not scale)

Set the number of cores (workers)

Protip: MRJob writes a lot of stuff into stderr; this suppresses it for clearer output for demonstration purposes

Looks about right

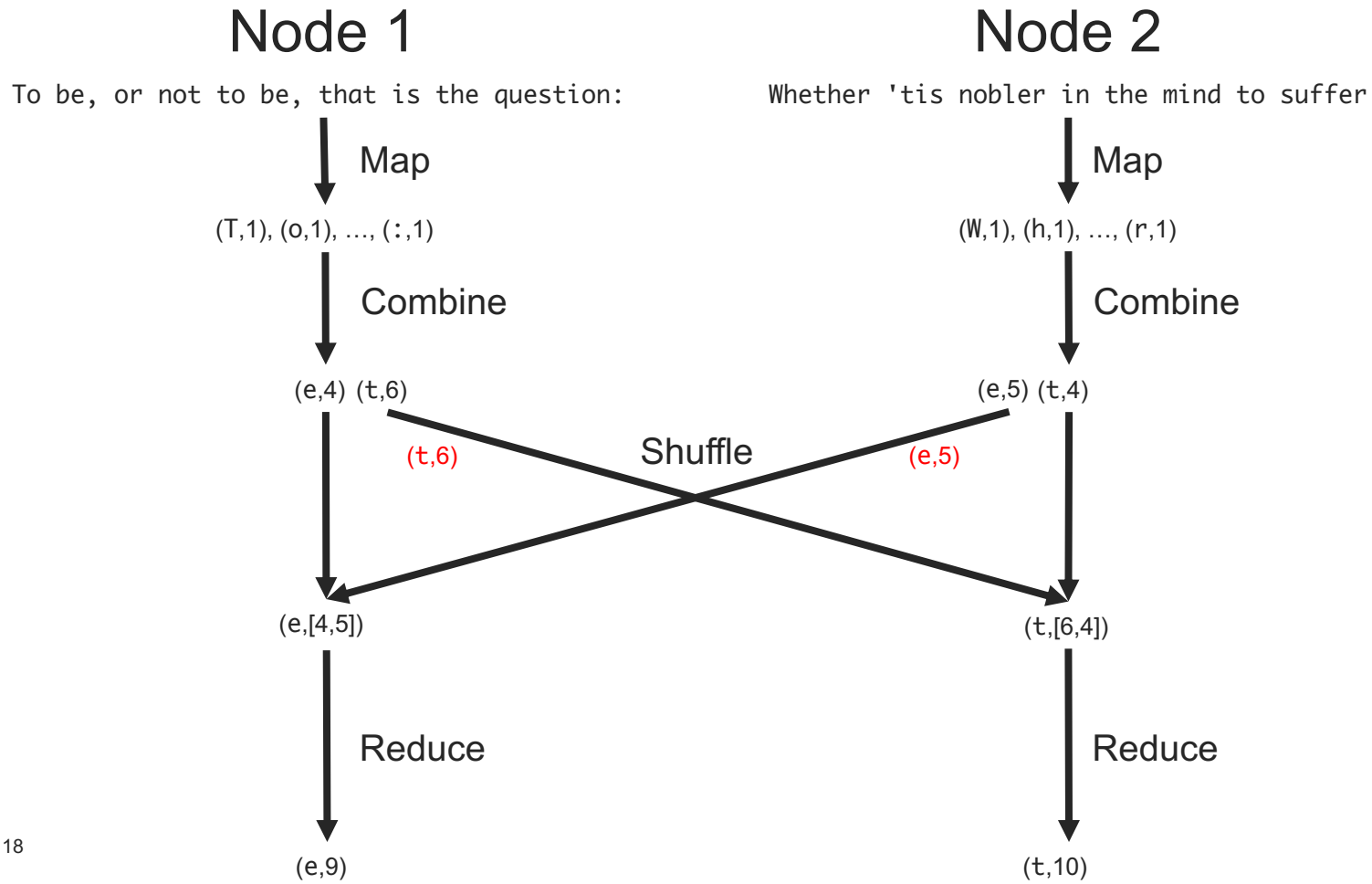
Performance considerations

- MapReduce only makes sense if the data is sufficiently large such that it cannot neatly fit in RAM
  - Then the framework solves the problem of coordinating work (although in a somewhat rigid way)
  - Computation is brought to the data, as compute is faster than I/O
  - If the data fits in RAM, then MapReduce only introduces unnecessary overhead
- The key to a performant MapReduce algorithm is to limit the amount of I/O
  - In practice: limit the amount of data that is communicated in the shuffling stage
- Storage of data matters
  - If the data is stored evenly distributed, we're good, but skewed distribution (e.g., all relevant pieces on one node) hurts parallelization

Combiners

- A problem with our example is that it can generate **a lot of** communication
  - Each occurrence of a letter is potentially communicated separately to another node
  - However, we only care about the **sum**: would it not be more efficient to just communicate the sum of counts on a node?
- **Combiners** solve this problem
- Combiners are essentially “mini-reducers” that are executed **locally** after the map operation but before shuffling
- Combiners perform a reduce operation locally, and only the result is then communicated
  - E.g., in this case, the combiner could simply count the sum of the occurrences locally

Execution example



Example

```
from mrjob.job import MRJob

class MRLettercount(MRJob):
    def mapper(self, _, line):
        for c in line:
            yield (c,1)

    def combiner(self, c, ones):
        yield (c,sum(ones))

    def reducer(self, c, counts):
        yield (c,sum(counts))

if __name__ == '__main__':
    MRLettercount.run()
```

```
(mrjob) karppa@CM-DWQ77WNX67 lecture6 % cat lines.txt | tee /dev/tty | python3 mrjob_lettercount2.py
-r local --num-cores 4 2> /dev/null
To be, or not to be, that is the question:
Whether 'tis nobler in the mind to suffer
"o"     7
"q"     1
"r"     4
"b"     3
"d"     1
"e"     9
"f"     2
"h"     5
"i"     5
"l"     1
"m"     1
"n"     5
":"     1
"T"     1
"W"     1
"a"     1
"s"     4
"t"     10
"u"     2
" "     16
"'"     1
","     2
```

Multiple steps

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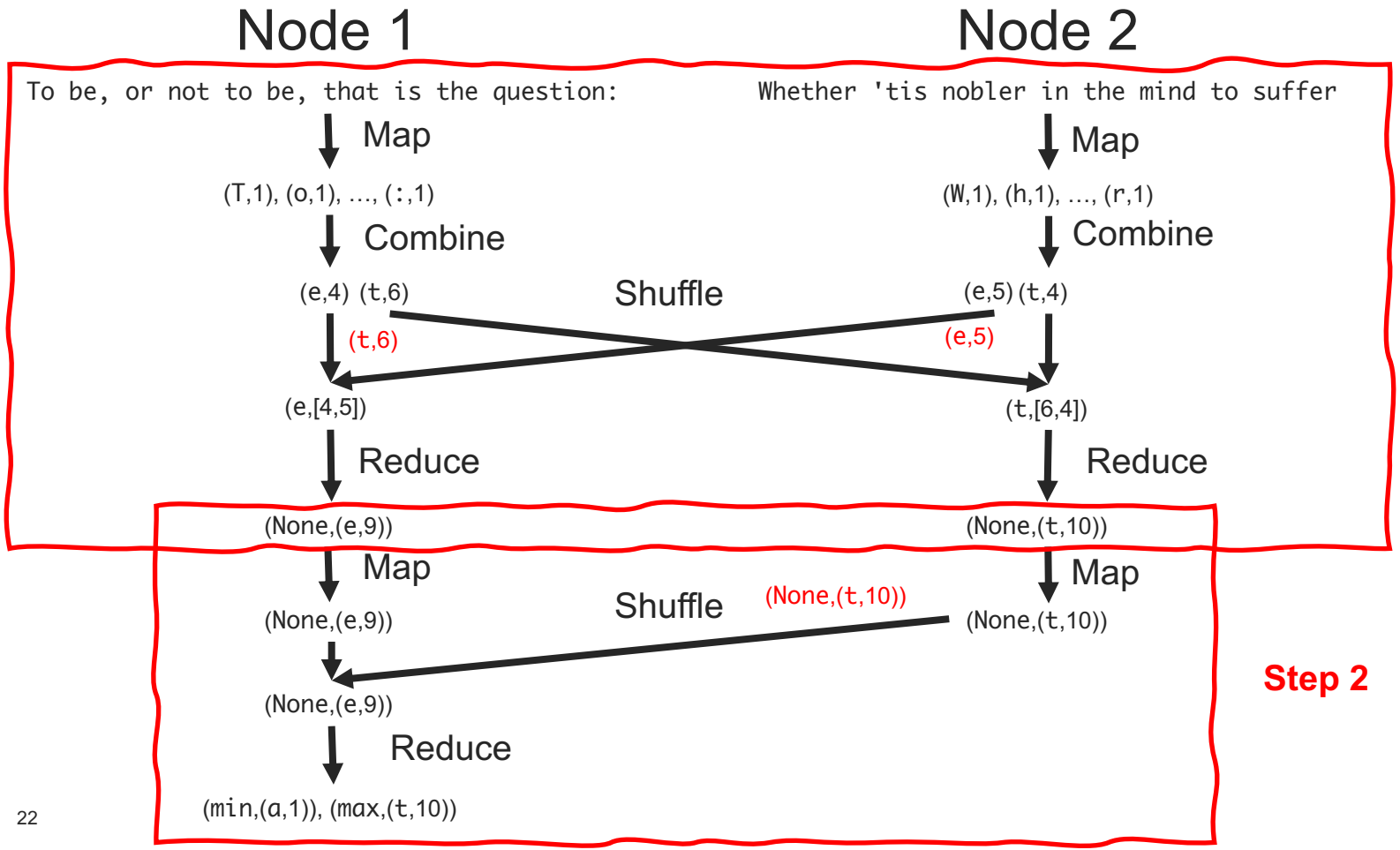
- What if we wanted to figure out the minimum, maximum, and average counts of characters?
- What if we wanted to figure out **which** characters have the minima and maxima counts?
- We can solve this by creating **multiple steps**
  - Each step is a MapReduce operation that is applied to the key-value pairs output by the previous step
- We change the first step such that we output the count of characters as **values**: (character,count)-tuples; we use a dummy key
- We don't really need a mapper in the second step as we only do another reduce step (mapper can be thought to be as the identity):
  - We traverse through the lists and identify the minima and maxima
- We return multiple key-value pairs to identify the identities and the values requested

Execution example



Steps in MRJob

- Multiple steps can be created by
  1. Implement all operations required as distinct member functions
  2. Implement the `steps()` function that returns a list of MRStep objects (each object defines the mapper, combiner, and reducer for the step)
  3. That's it!

```
from mrjob.job import MRJob
from mrjob.step import MRStep

class MRLettercount(MRJob):
    def mapper(self, _, line):
        for c in line:
            yield (c,1)

    def combiner(self, c, ones):
        yield (c,sum(ones))

    def reducer(self, c, counts):
        yield (None, (c,sum(counts)))

    def reducer2(self, _, charcounts):
        minimum = (None, float('inf'))
        maximum = (None, -1)
        numchars = 0
        total = 0
        for (c,count) in charcounts:
            numchars += 1
            total += count
            if count < minimum[1]:
                minimum = (c,count)
            if count > maximum[1]:
                maximum = (c,count)
        yield ('min', minimum)
        yield ('max', maximum)
        yield ('avg', total / numchars)

    def steps(self):
        return [MRStep(mapper=self.mapper, combiner=self.combiner,
                       reducer=self.reducer),
                MRStep(reducer=self.reducer2)]
```

Example

```
(mrjob) karppa@CM-DWQ77WNX67 lecture6 % cat lines.txt | tee /dev/tty | python3 mrjob_lettercount3.py
-r local --num-cores 4 2>/dev/null
To be, or not to be, that is the question:
Whether 'tis nobler in the mind to suffer
"min"   ["q",1]
"max"   [" ",16]
"avg"   3.772727272727273
```

Command line parameters

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- MRJob provides a basic `argparse`-compatible command-line interface
- Suppose we want to make it optional to only include ASCII characters in our word count, how would we do this?
- We implement the member function `configure_args()` and add a **passthrough** argument
- The argument is then available through `self.options`

Example

```
class MRLettercount(MRJob):
    def configure_args(self):
        super(MRLettercount, self).configure_args()
        self.add_passthru_arg(
            '--ascii-only', default=False, action='store_true',
            help='Only apply to ASCII characters')

    def mapper(self, _, line):
        if self.options.ascii_only:
            for c in line:
                if ord(c) < 128:
                    yield (c,1)
        else:
            for c in line:
                yield (c,1)
```

Required so that ordinary options are added as usual (call superclass version)

This adds the actual argument; note that this is exactly the same as using `argparse`

Args dictionary is available through self.options; it is exactly like the output of `parse_args`

Running MRJob programmatically

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- It was already mentioned that MRJob class files must not contain any other code
- This is related to the way they are handled by Hadoop
- If you want to run MRJob jobs manually (e.g., to instrumentate the code to be able to measure runtimes!), you will need to create a custom runner
- Do as follows:
  1. Construct your object, use the constructor argument `args` to pass the command-line parameters as usual (this can include your custom parameters)
  2. Construct the runner object with the member function `make_runner()` (idiom: use the with construction to gracefully close the object when it's finished)
  3. Use the `run()` member function of the runner to actually run the task
  4. Recover output using the `parse_output()` and `cat_output()` functions

Example

Use local runner (do this on bayes as well)

Construct the job

Set the number of cores

```
from mrjob_lettercount4 import MRLettercount
import time
import argparse

if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('-w', '--num-workers', type=int, default=1)
    parser.add_argument('filename')
    args = parser.parse_args()
    mr_job = MRLettercount(args=['-r', 'local', '--num-cores',
                                 str(args.num_workers), '--ascii-only',
                                 args.filename])
    start = time.time()
    with mr_job.make_runner() as runner:
        runner.run()
        for key, value in mr_job.parse_output(runner.cat_output()):
            print(key,value)
    end = time.time()
    print(f'Number of workers: {args.num_workers}')
    print(f'Time elapsed: {end-start} s')
```

Create runner, it will be closed graceully when it goes out of scope from the with block

Run the job

Custom arguments

Raw text output

Parse output into key-value pairs

Example

```
(mrjob) karppa@CM-DWQ77WNX67 lecture6 % python3 mrjob_lettercount_runner.py -w 4 ../lecture4/shakespe
are.txt
No configs specified for local runner
min ['\\', 1]
max [' ', 949869]
avg 61111.96511627907
Number of workers: 4
Time elapsed: 4.8429319858551025 s
```