Lecture 20: Hadoop and the mrjob package
Some slides adapted from C. Budak (UMichigan)
Recap

Previous lecture: Hadoop/MapReduce framework in general

This lecture: actually doing things

In particular: mrjob Python package
https://mrjob.readthedocs.io/en/latest/

Installation: pip install mrjob (or conda, or install from source...)

Recap: Basic concepts

**Mapper:** takes a (key,value) pair as input
  - Outputs zero or more (key,value) pairs
  - Outputs grouped by key

**Combiner:** takes a key and a subset of values for that key as input
  - Outputs zero or more (key,value) pairs
  - Runs after the mapper, only on a slice of the data
  - Must be idempotent

**Reducer:** takes a key and all values for that key as input
  - Outputs zero or more (key,value) pairs
Recap: a prototypical MapReduce program

Input

<k1,v1> → map → <k2,v2> → combine → <k2,v2'> → reduce → <k3,v3>

Output

Note: this output could be made the input to another MR program.
Recap: Basic concepts

**Step:** One sequence of map, combine, reduce
   All three are optional, but must have at least one!

**Node:** a computing unit (e.g., a server in a rack)

**Job tracker:** a single node in charge of coordinating a Hadoop job
   Assigns tasks to worker nodes

**Worker node:** a node that performs actual computations in Hadoop
   e.g., computes the Map and Reduce functions
Python mrjob package

Developed at Yelp for simplifying/prototyping MapReduce jobs

mrjob acts like a wrapper around Hadoop Streaming
Hadoop Streaming makes Hadoop computing model available to languages other than Java

But mrjob can also be run without a Hadoop instance at all!
e.g., locally on your machine
Why use mrjob?

Fast prototyping
   Can run locally without a Hadoop cluster...
   ...but can also run atop Hadoop or Spark

Much simpler interface than Java Hadoop

Sensible error messages
   i.e., usually there’s a Python traceback error if something goes wrong
Because everything runs “in Python”
MRJob.{mapper, combiner, reducer}

MRJob.mapper(key, value)

key – parsed from input; value – parsed from input.
Yields zero or more tuples of (out_key, out_value).

MRJob.combiner(key, values)

key – yielded by mapper; value – generator yielding all values from node corresponding to key.
Yields one or more tuples of (out_key, out_value)

MRJob.reducer(key, values)

key – key yielded by mapper; value – generator yielding all values from corresponding to key.
Yields one or more tuples of (out_key, out_value)

Basic *mrjob* script

```
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield "chars", len(line)
        yield "words", len(line.split())
        yield "lines", 1

    def reducer(self, key, values):
        yield key, sum(values)

if __name__ == '__main__':
    MRWC.run()
```
Basic mrjob script

mr_wc.py

```python
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield "chars", len(line)
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    def reducer(self, key, values):
        yield key, sum(values)

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

Contents of our example file.

```
keith@Steinhaus:~$ cat my_file.txt
Here is a first line.
And here is a second one.
Another line.
The quick brown fox jumps over the lazy dog.
keith@Steinhaus:~$

keith@Steinhaus:~$ python mr_wc.py my_file.txt
No configs found; falling back on auto-configuration
No configs specified for inline runner
Running step 1 of 1...
Creating temp directory
/tmp/mr_wc.keith.20171105.022629.949354
Streaming final output from
/tmp/mr_wc.keith.20171105.022629.949354/output[...
"chars"    103
"lines"    4
"words"    22
Removing temp directory
/tmp/mr_wc.keith.20171105.022629.949354...
keith@Steinhaus:~$
```
Basic `mrjob` script

```
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield "chars", len(line)
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    def reducer(self, key, values):
        yield key, sum(values)

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

Calling the `mrjob` program, with `my_file.txt` as input.
Basic mrjob script

```
from mrjob.job import MRJob

class MRWC(MRJob):
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        yield "chars", len(line)
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    def reducer(self, key, values):
        yield key, sum(values)

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

Logging information related to setup of Hadoop streaming.

```
No configs found; falling back on auto-configuration
No configs specified for inline runner
Running step 1 of 1...
Creating temp directory
/tmp/mr_wc.keith.20171105.022629.949354
Streaming final output from
/tmp/mr_wc.keith.20171105.022629.949354/output [...]"chars" 103
"lines" 4
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Removing temp directory
/tmp/mr_wc.keith.20171105.022629.949354...
```
Basic *mrjob* script

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    def reducer(self, key, values):
        yield key, sum(values)

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

Program output: number of characters, words and lines in the file.

```
keith@Steinhaus:~$ cat my_file.txt
Here is a first line.
And here is a second one.
Another line.
The quick brown fox jumps over the lazy dog.
keith@Steinhaus:~$

keith@Steinhaus:~$ python mr_wc.py my_file.txt
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Streaming final output from
/tmp/mr_wc.keith.20171105.022629.949354/output[...]

"chars"    103
"lines"    4
"words"    22
Removing temp directory
/tmp/mr_wc.keith.20171105.022629.949354...

keith@Steinhaus:~$
```
Basic mrjob script

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if __name__ == '__main__':
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```
keith@Steinhaus:~$ cat my_file.txt
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keith@Steinhaus:~$
```
Basic mrjob script

```
from mrjob.job import MRJob

class MRWC(MRJob):
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        yield "chars", len(line)
        yield "words", len(line.split())
        yield "lines", 1

    def reducer(self, key, values):
        yield key, sum(values)

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

This is a MapReduce job that counts the number of characters, words, and lines in a file.

Each mrjob program you write requires defining a class, which extends the MRJob class.

These mapper and reducer methods are precisely the Map and Reduce operations in our job. Recall the difference between the `yield` keyword and the `return` keyword.

This if-statement will run precisely when we call this script from the command line.
Basic `mrjob` script

This is a MapReduce job that counts the number of characters, words, and lines in a file.

mr_wc.py

```python
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield 'chars', len(line)
        yield 'words', len(line.split())
        yield 'lines', 1

    def reducer(self, key, values):
        yield key, sum(values)

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

MRJob class already provides a method `run()`, which `MRWordFrequencyCount` inherits, but we need to define at least one of `mapper`, `reducer` or `combiner`. 
Basic mrjob script

This is a MapReduce job that counts the number of characters, words, and lines in a file.

In mrjob, an MRJob object implements one or more steps of a MapReduce program. Recall that a step is a single Map->Reduce->Combine chain. All three are optional, but must have at least one in each step.

If we have more than one step, then we have to do a bit more work… (we’ll come back to this)

mr_wc.py

```python
from mrjob.job import MRJob

class MRWC(MRJob):
    Methods defining the steps go here.

if __name__ == '__main__':
    MRWC.run()
```
Basic `mrjob` script

`mr_wc.py`

```python
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield 'chars', len(line)
        yield 'words', len(line.split())
        yield 'lines', 1

    def reducer(self, key, values):
        yield key, sum(values)

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

Warning: do not forget these two lines, or else your script will not run!

This is a MapReduce job that counts the number of characters, words, and lines in a file.
Basic mrjob script: recap

```python
from mrjob.job import MRJob

class MRWC(MRJob):
    def mapper(self, _, line):
        yield "chars", len(line)
        yield "words", len(line.split())
        yield "lines", 1

    def reducer(self, key, values):
        yield key, sum(values)

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

After running the `mr_job` script with the following command:

```
keith@Steinhaus:~$ python mr_wc.py my_file.txt
```

The output is:

```
No configs found; falling back on auto-configuration
No configs specified for inline runner
Running step 1 of 1...
Creating temp directory
/tmp/mr_wc.keith.20171105.022629.949354
Streaming final output from
/tmp/mr_wc.keith.20171105.022629.949354/output...
"chars"    103
"lines"    4
"words"    22
Removing temp directory
/tmp/mr_wc.keith.20171105.022629.949354...
```
More complicated jobs: multiple steps

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

WORD_RE = re.compile(r"[\w']+")

class MRMostUsedWord(MRJob):
    def steps(self):
        return [
            MRStep(mapper=self.mapper_get_words,
                   combiner=self.combiner_count_words,
                   reducer=self.reducer_count_words),
            MRStep(reducer=self.reducer_find_max_word)]

def mapper_get_words(self, _, line):
    # yield each word in the line
    for word in WORD_RE.findall(line):
        yield (word.lower(), 1)

def combiner_count_words(self, word, counts):
    # optimization: sum the words we've seen so far
    yield (word, sum(counts))

def reducer_count_words(self, word, counts):
    # send all (num_occurrences, word) pairs to the same reducer.
    # num_occurrences is so we can easily use Python's max() function.
    yield None, (sum(counts), word)

    # discard the key; it is just None

def reducer_find_max_word(self, _, word_count_pairs):
    # so yielding one results in key=counts, value=word
    yield max(word_count_pairs)

if __name__ == '__main__':
    MRMostUsedWord.run()
```
To have more than one step, we need to override the existing definition of the method `steps()` in `MRJob`. The new `steps()` method must return a list of `MRStep` objects.

An `MRStep` object specifies a mapper, combiner and reducer. All three are optional, but must specify at least one.
First step: count words

This pattern should look familiar. It implements word counting.

One key difference, because this reducer output is going to be the input to another step.
Second step: find the largest count.

Note: `word_count_pairs` is like a list of pairs. Refer to how Python `max` works on a list of tuples.

```python
tuplist = [(1, 'cat'), (3, 'dog'), (2, 'bird')]
max(tuplist)
(3, 'dog')
```
from mrjob.job import MRJob
from mrjob.step import MRStep
import re

WORD_RE = re.compile(r"[\w']+")

class MRMostUsedWord(MRJob):
    def steps(self):
        return [
            MRStep(mapper=self.mapper_get_words,
                   combiner=self.combiner_count_words,
                   reducer=self.reducer_count_words),
            MRStep(reducer=self.reducer_find_max_word)]

    def mapper_get_words(self, self, _, line):
        # yield each word in the line
        for word in WORD_RE.findall(line):
            yield (word.lower(), 1)

    def combiner_count_words(self, self, word, counts):
        # optimization: sum the words we've seen so far
        yield (word, sum(counts))

    def reducer_count_words(self, self, word, counts):
        # send all (num_occurrences, word) pairs to the same reducer.
        # num_occurrences is so we can easily use Python's max() function.
        yield None, (sum(counts), word)

        # discard the key; it is just None
    def reducer_find_max_word(self, self, _, word_count_pairs):
        # each item of word_count_pairs is (count, word).
        # so yielding one results in key=counts, value=word
        yield max(word_count_pairs)

if __name__ == '__main__':
    MRMostUsedWord().run()
More complicated reducers: Python’s \texttt{reduce}

So far our reducers have used Python built-in functions \texttt{sum} and \texttt{max}.

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

class MRWC(MRJob):
    def mapper(self, _, line):
        yield "chars", len(line)
        yield "words", len(line.split())
        yield "lines", 1

    def reducer(self, key, values):
        yield key, sum(values)

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

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

class MRMostUsedWord(MRJob):
    def reducer_count_words(self, word, counts):
        # send all (num_occurrences, word) pairs to the same reducer.
        # num_occurrences is so we can easily use Python's \texttt{max()} function.
        yield None, (sum(counts), word)

    def reducer_find_max_word(self, _, word_count_pairs):
        # each item of word_count_pairs is (count, word),
        # so yielding one results in key=counts, value=word
        yield max(word_count_pairs)

if __name__ == '__main__':
    MRMostUsedWord.run()
```
More complicated reducers: Python’s \texttt{reduce}

So far our reducers have used Python built-in functions \texttt{sum} and \texttt{max}.

What if I want to multiply the values instead of \texttt{sum}?

Python does not have \texttt{product()} function analogous to \texttt{sum()}. . .

What if my values aren’t numbers, but I have a sum defined on them? e.g., tuples representing vectors

Want \((a, b) + (x, y) = (a+x, b+y)\), but tuples don’t support this addition.

\textbf{Solution: use} \texttt{functools.reduce}
More complicated reducers: Python’s `reduce`

```
from mrjob.job import MRJob

class MRBigProduct(MRJob):
    # Return the product of all the numbers.

    def mapper(self, _, line):
        # Assume that file is one number per line.
        number = float(line.strip())
        yield None, number

    def reducer(self, _, values):
        yield None, reduce(lambda x,y: x*y, values, 1.0)

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

Using `reduce` and `lambda`, we can get just about any reducer we want.

**Note:** this example was run in Python 2. You’ll need to import `functools` to do this in Python 3.
Note: numbers are successfully extracted from input and multiplied with one another.
Running mrjob on a Hadoop cluster

We’ve already seen how to run mrjob from the command line. Previous examples emulated Hadoop But no actual Hadoop instance was running!

That’s fine for prototyping and testing…

...but how do I actually run it on a Hadoop cluster?

We need access to a computer cluster!
This semester, we will use Google Cloud Platform.
Overview: Google Cloud

Google Cloud Platform (GCP) is Google’s distributed computing service
- Cloud computing: rent computers (and storage) by the minute
- ML tools (e.g., support for TensorFlow and related tools)
- Large-scale database (e.g., HDFS and HBase for Hadoop)

Dataproc: Google’s service for running Apache Hadoop jobs

Homework 11 will walk you through the process of running your mrjob program on a GCP Dataproc cluster (i.e., Hadoop server).

Step 1: access Google Cloud console, which gives a terminal in which to interact with Google Cloud. 
https://console.cloud.google.com/
Running `mrjob` on a cluster

```
keith@cloudshell:~$ python2 mr wc.py myfile.txt -r dataproc
No configs found; falling back on auto configuration
No configs specified for dataproc runner
using existing temp bucket mrjob-us-west1-94b1020a1dfb26ce
[More logging information, redacted for space]
[...]
Streaming final output from gs://mrjob-us-west1-94b1020a1dfb26ce/tmp/mr_wc.kdlevin.20210403.050421.847299/output/…
"chars" 103
"lines" 4
"words" 22
Removing temp directory /tmp/mr_wc.kdlevin.20210403.050421.847299...
Attempting to terminate cluster
Successfully terminated
keith@cloudshell:~$
```

On a compute cluster, we call `mrjob` just like on our local machine.
Running `mrjob` on a cluster

```
keith@cloudshell:~$ python2 mr wc.py myfile.txt -r dataproc
No configs found; falling back on auto-configuration
No configs specified for dataproc runner
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[More logging information, redacted for space]
[...]
Streaming final output from gs://mrjob-us-west1-94b1020a1dfb26ce/tmp/mr_wc.kdlevin.20210403.050421.847299/output/...
"chars" 103
"lines" 4
"words" 22
Removing temp directory /tmp/mr wc.kdlevin.20210403.050421.847299...
Attempting to terminate cluster
cluster mrjob-us-west1-0249c94657283a00 successfully terminated
keith@cloudshell:~$
```

One important difference: need to specify that we want to run on the Hadoop cluster
Running `mrjob` on a cluster

```
keith@cloudshell:~$ python2 mr_wc.py myfile.txt -r dataproc
No configs found; falling back on auto-configurationNo configs specified for dataproc runner using existing temp bucket mrjob-us-west1-94b1020a1dfb26ce
[More logging information, redacted for space]
[...]
Streaming final output from gs://mrjob-us-west1-94b1020a1dfb26ce/tmp/mr_wc.kdlevin.20210403.050421.847299/output/...
"chars" 103
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Removing temp directory /tmp/mr_wc.kdlevin.20210403.050421.847299... Attempting to terminate cluster cluster mrjob-us-west1-0249c94657283a00 successfully terminated
keith@cloudshell:~$
```

You'll see a bit more logging information than you're used to from before...
Running `mrjob` on a cluster

```
keith@cloudshell:~$ python2 mr_wc.py myfile.txt -r dataproc
No configs found; falling back on auto-configuration
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keith@cloudshell:~$
```

But output will still include your key-value pairs.
mrjob hides complexity of MapReduce

We need only define mapper, reducer, combiner

Package handles everything else
   Most importantly, interacting with Hadoop

But mrjob does provide powerful tools for specifying Hadoop configuration

You don’t have to worry about any of this in this course, but you should be aware of it in case you need it in the future.
**mrjob: protocols**

**mrjob** assumes that all data is “newline-delimited bytes”

That is, newlines separate lines of input

Each line is a single unit to be processed in isolation

(e.g., a line of words to count, an entry in a database, etc)

**mrjob** handles inputs and outputs via **protocols**

**Protocol** is an object that has `read()` and `write()` methods

`read()`: convert bytes to (key,value) pairs

`write()`: convert (key,value) pairs to bytes
**mrjob: protocols**

Controlled by setting three variables in config file `mrjob.conf`:

- `INPUT_PROTOCOL`, `INTERNAL_PROTOCOL`, `OUTPUT_PROTOCOL`

**Defaults:**

```python
INPUT_PROTOCOL = mrjob.protocol.RawValueProtocol
INTERNAL_PROTOCOL = mrjob.protocol.JSONProtocol
OUTPUT_PROTOCOL = mrjob.protocol.JSONProtocol
```

Again, you don’t have to worry about this in this course, but you should be aware of it.

Data passed around internally via JSON. This is precisely the kind of thing that JSON is good for.