MIDS-W261-2016-HWK-Week09-DangSeltzer

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- **Course**: 2016-0111 DATASCI W261: Machine Learning at Scale
- **Section**: Spring 2016, Section 2
- **Assignment**: Homework 9, Week 9
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In [ ]:
```
%%javascript
require(['base/js/utils'], function(utils) {
    utils.load_extensions('usability/ruler/main');
    utils.load_extensions('usability/toc2/main');
    utils.load_extensions('usability/toggle_all_line_numbers/main');
    utils.load_extensions('autosaveclasses');
});
```

```
<IPython.core.display.Javascript object>
```

1 MRJob driver helper utilities

1.1 Notebook imports

If the following cell (which imports all the Python packages used by the different drivers) doesn't run, some of the drivers and helper functions in the notebook will also fail to run. Note that you will also need `mrjob` to run the actual jobs themselves.

In [ ]:
```
%matplotlib inline

from __future__ import division
from collections import defaultdict, OrderedDict
from datetime import datetime
import functools
from IPython.display import display
import json
import math
import matplotlib
import networkx
import numpy
import os
import pandas
import subprocess
import sys

pandas.set_option('display.precision', 4)
pandas.set_option('display.max_rows', 200)
```

1.2 Hadoop settings

The following settings are used by the Hadoop jobs scattered throughout the notebook and should be updated to reflect the size of your Hadoop cluster.

In [ ]:
```
hdfs_base_folder = '/user/ubuntu'
mapper_count = 32
reducer_count = 32
debug_output = '/dev/null'
```

1.3 File management utilities

Different runner types have keep their files in different locations. These utility methods allow us to get some uniformity in the scripts since it will return the actual paths needed by different runner types.

In [ ]:
```
"""
Returns whether the given file path corresponds to something on the file system used by
the given runner.
"""
def file_exists(runner_type, name):
    if runner_type in ['inline', 'local']:
        return os.path.isfile(name)

    status = subprocess.call([
        'hdfs', 'dfs', '-test', '-f', hdfs_base_folder + '/' + name
    ])

    return status == 0

"""
Returns whether the given file path corresponds to something on the file system used by
the given runner.
"""
def folder_exists(runner_type, name):
    if runner_type in ['inline', 'local']:
        return os.path.isdir(name)

    status = subprocess.call([
        'hdfs', 'dfs', '-test', '-d', hdfs_base_folder + '/' + name
    ])

    return status == 0

"""
Removes the folder located at the given path. Note that it does a recursive remove, so it
doesn't throw an error if it's a file (it will still delete it).
"""
def remove_folder(runner_type, folder_name):
    if runner_type in ['inline', 'local']:
        !rm -rf $folder_name
    else:
        !hdfs dfs -rm -r -f -skipTrash $hdfs_base_folder/$folder_name

"""
Returns an appropriate file path to pass to a runner as an input/output folder.
```

```
"""
def get_mrjob_path(runner_type, folder_name):
    if folder_name is None or folder_name == '':
        return ''

    if runner_type in ['inline', 'local']:
        return folder_name

    return 'hdfs://' + hdfs_base_folder + '/' + folder_name
```

1.4 File download utilities

Since the URLs for the files tend to be very long, first we create some utility methods which make it more clear what we're doing when we're downloading data from either Dropbox or Amazon S3.

In [ ]:
```
"""
Utility method to split the file to make sure that multiple mapper tasks (and hopefully
multiple reducer tasks) get created for our jobs in Hadoop.
"""
def split_for_hdfs(file_name, target_folder = None):
    if target_folder is None:
        target_folder = file_name

    if folder_exists('hadoop', target_folder):
        return

    !mkdir -p /run/shm/$target_folder
    !split $file_name -l 100000 /run/shm/$target_folder/

    !hdfs dfs -mkdir -p $target_folder
    !hdfs dfs -copyFromLocal /run/shm/$target_folder/* $hdfs_base_folder/$target_folder

    !rm -rf /run/shm/$target_folder

"""
Utility method which downloads a Dropbox file from the folder for this assignment.
"""
def get_dropbox_file(dropbox_folder_name, folder_name, file_name):
    !mkdir -p input/$folder_name
    target_file_path = 'input/%s/%s' % (folder_name, file_name)

    if os.path.isfile(target_file_path):
        return target_file_path

    dropbox_url = 'https://www.dropbox.com/sh'
    !curl -Ls $dropbox_url/$dropbox_folder_name/$file_name > $target_file_path

    return target_file_path

"""
Utility method which downloads a file from an S3 bucket for this assignment.
"""
def get_s3_file(folder_name, file_name):
    !mkdir -p input/$folder_name
    target_file_path = 'input/%s/%s' % (folder_name, file_name)
```

```
    if os.path.isfile(target_file_path):
        return target_file_path

    !aws s3 --region us-west-2 cp \
        s3://ucb-mids-mls-networks/$folder_name/$file_name \
        $target_file_path

    return target_file_path
```

1.5 Content retrieval utilities

We also sometimes need to grep a file or `wc -l` the output. The following functions allow us to do so in a runner-agnostic way within the code itself by handling the runner-specific logic here.

In [ ]:
```
"""
Pipes the standard output for the cat command to the given command and returns the result.
"""
def pipe_cat_output(runner_type, path, command = 'cat'):
    if file_exists(runner_type, path):
        cat_path = path
    elif folder_exists(runner_type, path):
        cat_path = path + '/*'
    else:
        return None

    if runner_type in ['inline', 'local']:
        result = !cat $cat_path | $command
    else:
        result = !hdfs dfs -cat $hdfs_base_folder/$cat_path | $command

    return '\n'.join(result)

"""
Returns the total number of lines in all files contained in the specified folder.
"""
def get_line_count(runner_type, folder_name):
    return int(pipe_cat_output(runner_type, folder_name, 'wc -l'))

"""
Returns the lines in the specified folder starting with the specified key. This can be
parsed by the runner to yield the original key and value.
"""
def get_lines_with_key(runner_type, folder_name, key):
    return pipe_cat_output(runner_type, folder_name, 'grep "^' + key + '"')
```

2 HW 9.0: Short answer questions

2.1 HW 9.0a

What is PageRank and what is it used for in the context of web search?

PageRank is one of the ranking algorithms used by Google that was introduced by Sergey Brin and Lawrence Page in their paper, The Anatomy of a Large-Scale Hypertextual Web Search Engine. At a high level, it provides a measure of "popularity" of pages, due to the underlying assumption that important websites are likely to have more incoming links than unimportant websites.

Because it identifies popular pages, PageRank has several applications in web search.

- PageRank can be used to influence the priority with which web sites are crawled.
- PageRank can be used to provide informed data compression, as popular sites that often come up in search results will require less bits in order to retrieve from disk or transfer over the network.
- PageRank can be used in order to identify an ordering of pages in the inverted index. This allows popular pages arrive first in general search results without additional sorting at query time.

2.2 HW 9.0b

> What modifications have to be made to the webgraph in order to leverage the machinery of Markov Chains to compute the steady state distribution?

The transformation are described in more detail in the Wikipedia article, Google matrix.

First, we represent the process of visiting pages as a Markov process. To do this, we suggest a random surfer model, wherein a web surfer has some probability of choosing one of the outgoing links on the page. To achieve this, each edge in the webgraph is given a weight that is proportional to the total number of outgoing edges from the source node. We define the weight of the edge as $\frac{1}{k}$, where k is the number of outgoing edges for a given node. This results in the sum of the probabilities being 1.

The first problem in the webgraph is dangling nodes (nodes with no outgoing edges), as they will not re-distribute their mass (thus effectively creating a sink). In order to address this problem, we update the webgraph so that from a dangling node, you transition to any other node in the webgraph with uniform probability. This results in these sink nodes being given edges with weight $\frac{1}{n}$, where n is the number of nodes in the web graph.

The second problem in the webgraph is the large number of zero probabilities, making it difficult to prove the existence of a steady state distribution. To address this, we introduce a "teleportation" factor that re-scales the webgraph by a damping factor d. We then recapture the $(1-d)$ mass lost by the scaling and redistribute it to the n nodes of the web graph, thus giving each node $\frac{1-d}{n}$ and eliminate all zeroes in the matrix.

Together, this results in a Markov matrix since the entries will be strictly positive (Perron-Frobenius theorem).

2.3 HW 9.0c

> OPTIONAL: In topic-specific pagerank, how can we insure that the irreducible property is satified? (HINT: see HW9.4)

In topic-specific PageRank, we can ensure that the irreducible property (strong connectedness) is achieved by scaling the non-uniform teleport factor used by topic-specific PageRank by a factor $\beta \in (0, 1)$ and recapture the $(1-\beta)$ mass lost in this scaling by redistributing it to the $n - |T_j|$ nodes with zero values. We can treat this the same way as the teleport factor and do so uniformly.

To retain the topic-specific qualities of topic-specific page rank, β must be close to 1 (thus the redistributed mass is very small). Otherwise, we will wind up with anti-topic specific page rank (giving more teleportation weight to pages that are NOT about our topic).

3 HW 9.1: MRJob implementation of basic PageRank

This job requires us to do several things: - Find all nodes in the graph (dangling nodes will not have an explicit neighbors list) - For each node, maintain graph structure and initialize PageRank to $\frac{1}{n}$

3.1 Identify dangling nodes

Some of the PageRank tasks in the homework require that have the dangling nodes included as input when processing the graph, but they are often missing. The following jobs perform a join between the in-degree node table and the out-degree node table to allow us to fix that.

3.1.1 Create MRJob to tag tables for join

First, we need to tag the different tables so that as we process the input, we know what table we are interacting with.

In [ ]:
```
from mrjob.job import MRJob
from mrjob.protocol import ReprProtocol
from mrjob.step import MRStep
import sys

class TagWithTableNameJob(MRJob):

    OUTPUT_PROTOCOL = ReprProtocol

    def configure_options(self):
        super(TagWithTableNameJob, self).configure_options()
        self.add_passthrough_option('--mapper-count', default=1)
        self.add_passthrough_option('--table-name')

    """
    Add the table name as part of the value.
    """
    def mapper(self, _, line):
        name, value = line.split('\t', 1)
        yield name, (self.options.table_name, eval(value))

    """
    Set the mapper count options to make sure that MRJob creates enough mapper tasks.
    """
    def steps(self):
        step = MRStep(
            mapper = self.mapper,
            jobconf = {
                'mapreduce.job.maps': self.options.mapper_count
            })

        return [step]

if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
    job = TagWithTableNameJob()
    job.run()
```

Add a utility function to make it easy to call.

In [ ]:
```
def tag_with_table_name_job(runner_type, graph_file, table_name):
    if graph_file is None:
        return None

    table_file = graph_file + '.table'
```

```
    remove_folder(runner_type, table_file)

    mrjob_graph_file = get_mrjob_path(runner_type, graph_file)
    mrjob_table_file = get_mrjob_path(runner_type, table_file)

    !python TagWithTableNameJob.py \
        -r $runner_type \
        --strict-protocols \
        --no-bootstrap-mrjob \
        --no-output \
        --table-name $table_name \
        --output-dir $mrjob_table_file \
        --mapper-count $mapper_count \
        $mrjob_graph_file \
        2>> $debug_output

    return table_file
```

3.1.2 Create MRJob to add dangling nodes

Dangling node identification is effectively a full outer join in the sense that we will emit the key as long as it appears in either table, but we only emit the values from the left table (we drop any values from the right table).

In [ ]:
```
from mrjob.job import MRJob
from mrjob.step import MRStep
from mrjob.protocol import ReprProtocol
import sys

class AddDanglingNodesJob(MRJob):

    INPUT_PROTOCOL = ReprProtocol
    INTERNAL_PROTOCOL = ReprProtocol
    OUTPUT_PROTOCOL = ReprProtocol

    def configure_options(self):
        super(AddDanglingNodesJob, self).configure_options()
        self.add_passthrough_option('--left-table')
        self.add_passthrough_option('--right-table')

        self.add_passthrough_option('--mapper-count', type='int', default=1)
        self.add_passthrough_option('--reducer-count', type='int', default=1)

    """
    If you are joining with yourself, that means we didn't have a file which gives you
    degrees for the other table. In this case, we will emit our neighbors in order to
    effectively derive the other table.
    """
    def mapper_init(self):
        self.derive_right_table = self.options.left_table == self.options.right_table

    """
    We are only interested in generating what the left table will be. Therefore, we will
    emit the full entries of the left table, but only an empty value for the right table.
```

```
        """
        def mapper(self, name, table_row):
            table_name, neighbors = table_row

            if self.options.left_table == table_name:
                yield name, neighbors
            else:
                yield name, {}

            # If we have to derive the right table, we'll emit each of our neighbors.

            if self.derive_right_table:
                for neighbor_name, degree in neighbors.iteritems():
                    yield neighbor_name, {}

        """
        Emit the left table row if found, and emit the blank entry if only right table entries
        were found (dangling node).
        """
        def reducer(self, name, all_neighbors):
            emit_neighbors = {}

            for neighbors in all_neighbors:
                if len(neighbors) != 0:
                    emit_neighbors = neighbors

            yield name, emit_neighbors

        """
        Configure the reducer as a combiner and set the mapper and reducer count options to
        make sure that MRJob creates enough mapper/reducer tasks.
        """
        def steps(self):
            step = MRStep(
                mapper_init = self.mapper_init, mapper = self.mapper,
                combiner = self.reducer, reducer = self.reducer,
                jobconf = {
                    'mapreduce.job.maps': self.options.mapper_count,
                    'mapreduce.job.reduces': self.options.reducer_count,
                    'mapreduce.map.output.compress': 'true',
                    'mapred.map.output.compress.codec': \
                        'org.apache.hadoop.io.compress.SnappyCodec'
                })

            return [step]

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = AddDanglingNodesJob()
        job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def add_dangling_nodes_job(runner_type, out_nodes_graph, in_nodes_graph):

            # Tag the tables so that we can perform the join
```

```
if out_nodes_graph is None:
    print 'Failed to create a tagged graph for', out_nodes_graph
    return

out_nodes_table = tag_with_table_name_job(runner_type, out_nodes_graph, 'out')

if out_nodes_table is None:
    print 'Failed to create a tagged graph for', out_nodes_graph
    return

in_nodes_table = tag_with_table_name_job(runner_type, in_nodes_graph, 'in')

if in_nodes_table is None and in_nodes_graph is not None:
    print 'Failed to create a tagged graph for', in_nodes_graph
    return

# If we are missing one of the tables, we'll join the table with itself

left_table = 'out'
right_table = 'in'

if in_nodes_graph is None:
    right_table = 'out'
    in_nodes_table = ''

# Now we run the job with all the tables we've created

new_nodes_graph = out_nodes_graph + '.all'
remove_folder(runner_type, new_nodes_graph)

mrjob_out_nodes_table = get_mrjob_path(runner_type, out_nodes_table)
mrjob_in_nodes_table = get_mrjob_path(runner_type, in_nodes_table)
mrjob_new_nodes_graph = get_mrjob_path(runner_type, new_nodes_graph)

!python AddDanglingNodesJob.py \
    -r $runner_type \
    --strict-protocols \
    --no-bootstrap-mrjob \
    --no-output \
    --left-table $left_table \
    --right-table $right_table \
    --mapper-count $mapper_count \
    --reducer-count $reducer_count \
    --output-dir $mrjob_new_nodes_graph \
    $mrjob_out_nodes_table $mrjob_in_nodes_table \
    2>> $debug_output

return new_nodes_graph
```

3.2 Create PageRank MRJob

Write a basic MRJob implementation of the iterative PageRank algorithm that takes sparse adjacency lists as input (as explored in HW 7).

Make sure that you implementation utilizes teleportation (1-damping/the number of nodes in the network), and further, distributes the mass of dangling nodes with each iteration so that the output of each iteration is correctly normalized (sums to 1).

[NOTE: The PageRank algorithm assumes that a random surfer (walker), starting from a random web page, chooses the next page to which it will move by clicking at random, with probability d, one of the hyperlinks in the current page. This probability is represented by a so-called 'damping factor' d, where $d \in (0, 1)$. Otherwise, with probability $(1 - d)$, the surfer jumps to any web page in the network. If a page is a dangling end, meaning it has no outgoing hyperlinks, the random surfer selects an arbitrary web page from a uniform distribution and "teleports" to that page]

In this job we need to do the following:

- Distribute a node's PageRank to its neighbors
- Distribute the mass of dangling nodes, and account for teleporting

Distribute node's PageRank to neighbors For each node we encounter, we have the current PageRank (let's call this $\mathrm{PR}_{\mathrm{old}}$), and the list of neighbors. We need to divide the PageRank by the number of neighbors, and emit this to each neighbor. If there are no neighbors, we cannot emit the PageRank anywhere, so we accumulate it. Once we accumulate the distributed PageRank mass in each node, we have a preliminary PageRank for each node, which we can denote as $\mathrm{PR}_{\mathrm{int}}$.

Distribute the mass of dangling nodes and account for teleporting We have accumulated the total PageRank mass that has not yet been distributed, because there were no neighbors to distribute the mass to. We also need to account for teleporting. Given the dangling mass, m, and the damping factor, α, and n nodes, we have the following:

$$\mathrm{PR}_{\mathrm{new}} = (1 - \alpha)\left(\frac{1}{n}\right) + \alpha\left(\frac{m}{n} + \mathrm{PR}_{\mathrm{int}}\right)$$

3.2.1 Implement PageRank algorithm

First, we want a job that will perform a single iteration of the page rank computation where it will determine the updated page rank based on the rank contribution from all incoming nodes and from random teleport. We also include the known dangling mass from the previous iteration of the algorithm (or, the uniform number of dangling nodes.

```
In [ ]: from __future__ import division
        import json
        from mrjob.job import MRJob
        from mrjob.protocol import ReprProtocol
        from mrjob.step import MRStep
        import sys

        class PageRankSingleIterationJob(MRJob):

            INPUT_PROTOCOL = ReprProtocol
            INTERNAL_PROTOCOL = ReprProtocol
            OUTPUT_PROTOCOL = ReprProtocol

            def configure_options(self):
```

```
        super(PageRankSingleIterationJob, self).configure_options()

        self.add_passthrough_option('--damping-factor', type='float', default=0.85)

        self.add_passthrough_option('--mapper-count', type='int', default=1)
        self.add_passthrough_option('--reducer-count', type='int', default=1)

    """
    Does nothing here, but can be overridden by sub-classes.
    """
    def load_data(self):
        with open('node_count.txt', 'r') as node_count_file:
            self.node_count = json.load(node_count_file)

        with open('dangling_mass.txt', 'r') as dangling_mass_file:
            self.dangling_mass = json.load(dangling_mass_file)

    """
    Distribute the mass to your neighbors, making sure to emit your own information so
    that is available in the next iteration.
    """
    def mapper(self, key, node_data):

        old_page_rank, neighbors, metadata = self.parse_node_data(key, node_data)

        # Emit yourself with a page rank contribution of zero, but with your neighbors
        # and your old page rank. This allows information to persist between iterations.

        yield str(key), (self.get_empty_mass(), old_page_rank, neighbors, metadata)

        # If you have no neighbors, then you are part of the dangling probability mass.

        neighbor_count = len(neighbors)

        if neighbor_count == 0:
            return

        # Otherwise, redistribute your probability mass to your neighbors.

        distributed_mass = self.get_distributed_mass(key, old_page_rank, neighbor_count)

        for neighbor_name in neighbors.iterkeys():
            yield neighbor_name, (distributed_mass, self.get_empty_mass(), None, None)

    """
    Give all nodes uniform probability in the initial case.
    """
    def parse_node_data(self, key, node_data):
        if isinstance(node_data, dict):
            old_page_rank = 1.0 / self.node_count
            neighbors = node_data
        else:
            old_page_rank = node_data[0]
            neighbors = node_data[2]
```

```python
        return old_page_rank, neighbors, None

    """
    Distribute mass evenly across all neighbors.
    """
    def get_distributed_mass(self, key, old_page_rank, neighbor_count):
        return old_page_rank / neighbor_count

    """
    Combine the contributions from each node to reduce network usage.
    """
    def combiner(self, key, all_node_data):
        emit_new_rank = self.get_empty_mass()
        emit_old_rank = self.get_empty_mass()
        emit_neighbors = None
        emit_metadata = None

        for new_rank, old_rank, neighbors, metadata in all_node_data:
            emit_new_rank = self.get_merged_mass(emit_new_rank, new_rank)
            emit_old_rank = self.get_merged_mass(emit_old_rank, old_rank)

            if neighbors is not None:
                emit_neighbors = neighbors

            if metadata is not None:
                emit_metadata = metadata

        yield key, (emit_new_rank, emit_old_rank, emit_neighbors, emit_metadata)

    """
    Returns 0
    """
    def get_empty_mass(self):
        return 0.0

    """
    Sum the values together.
    """
    def get_merged_mass(self, old_mass, new_mass):
        return old_mass + new_mass

    """
    Combine the mass from all neighbors. Include mass coming from teleportation, which is
    both from regular nodes (which dedicate part of their mass to teleportation) and from
    dangling nodes (which dedicate all of their mass to teleportation).
    """
    def reducer(self, key, all_node_data):
        emit_new_rank = self.get_empty_mass()
        emit_old_rank = self.get_empty_mass()

        emit_neighbors = {}
        emit_metadata = None
```

```python
        # Compute the base page rank from incoming nodes.

        for new_rank, old_rank, neighbors, metadata in all_node_data:
            emit_new_rank = self.get_merged_mass(emit_new_rank, new_rank)
            emit_old_rank = self.get_merged_mass(emit_old_rank, old_rank)

            if neighbors is not None:
                emit_neighbors = neighbors

            if metadata is not None:
                emit_metadata = metadata

        # Apply the damping factor to the accumulated mass

        emit_new_rank = self.get_damped_mass(emit_new_rank)

        # Compute the contribution from the dangling mass and the teleport factor.

        if self.options.damping_factor != 1.0:
            dangling_bonus = self.get_dangling_bonus(key, emit_metadata)
            teleport_bonus = self.get_teleport_bonus(key, emit_metadata)

            emit_new_rank = self.get_merged_mass(emit_new_rank, dangling_bonus)
            emit_new_rank = self.get_merged_mass(emit_new_rank, teleport_bonus)

        yield key, (emit_new_rank, emit_old_rank, emit_neighbors, emit_metadata)

    """
    Damped mass is scaled directly since we have a scalar value.
    """
    def get_damped_mass(self, emit_mass):
        return self.options.damping_factor * emit_mass

    """
    Dangling bonus is uniform.
    """
    def get_dangling_bonus(self, key, metadata):
        return self.options.damping_factor * self.dangling_mass / self.node_count

    """
    Teleport bonus is uniform and comes from every node.
    """
    def get_teleport_bonus(self, key, metadata):
        teleport_factor = 1.0 - self.options.damping_factor
        teleport_mass = teleport_factor / self.node_count
        return teleport_mass

    """
    Set the mapper and reducer count options to make sure that MRJob creates enough
    mapper/reducer tasks.
    """
    def steps(self):
        step = MRStep(
            mapper_init = self.load_data, mapper = self.mapper, combiner = self.combiner,
```

```
                reducer_init = self.load_data, reducer = self.reducer,
                jobconf = {
                    'mapreduce.job.maps': self.options.mapper_count,
                    'mapreduce.job.reduces': self.options.reducer_count,
                    'mapreduce.map.output.compress': 'true',
                    'mapred.map.output.compress.codec': \
                        'org.apache.hadoop.io.compress.SnappyCodec'
                })

            return [step]

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = PageRankSingleIterationJob()
        job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def page_rank_single_iteration_job(
            python_file, runner_type, graph_file, output_folder, damping_factor):

            mrjob_graph_file = get_mrjob_path(runner_type, graph_file)
            mrjob_output_folder = get_mrjob_path(runner_type, output_folder)

            !python $python_file \
                -r $runner_type \
                --strict-protocols \
                --no-bootstrap-mrjob \
                --no-output \
                --file node_count.txt \
                --file dangling_mass.txt \
                --damping-factor $damping_factor \
                --mapper-count $mapper_count \
                --reducer-count $reducer_count \
                --output-dir $mrjob_output_folder \
                $mrjob_graph_file \
                2>> $debug_output
```

3.2.2 Implement post-job computations

Next, we need to compute the probability mass associated with dangling nodes so that we can properly update our page rank computation, factoring in teleportation. Additionally, we want to check for convergence.

```
In [ ]: from __future__ import division
        import json
        from mrjob.job import MRJob
        from mrjob.protocol import ReprProtocol
        from mrjob.step import MRStep
        import sys

        class CheckPageRankConvergenceJob(MRJob):

            INPUT_PROTOCOL = ReprProtocol
            INTERNAL_PROTOCOL = ReprProtocol
            OUTPUT_PROTOCOL = ReprProtocol
```

```python
def configure_options(self):
    super(CheckPageRankConvergenceJob, self).configure_options()
    self.add_passthrough_option('--mapper-count', type='int', default=1)

def mapper_init(self):
    with open('node_count.txt', 'r') as node_count_file:
        self.node_count = json.load(node_count_file)

    self.dangling_mass = self.get_empty_mass()
    self.squared_rank_change = self.get_empty_mass()

"""
Accumulate the probability mass from nodes that have no outgoing links as well as the
change in rank.
"""
def mapper(self, key, node_data):
    new_page_rank, old_page_rank, neighbors, metadata = self.parse_node_data(
        key, node_data)

    if len(neighbors) == 0:
        dangling_mass = self.get_dangling_mass(new_page_rank, metadata)

        self.dangling_mass = self.get_merged_mass(
            self.dangling_mass, dangling_mass)

    squared_rank_change = self.get_squared_rank_change(
        new_page_rank, old_page_rank)

    self.squared_rank_change = self.get_merged_mass(
        self.squared_rank_change, squared_rank_change)

"""
If we just initialized, there's no page rank to speak of. Otherwise, extract the
metadata from the fields.
"""
def parse_node_data(self, key, node_data):
    if isinstance(node_data, dict):
        new_page_rank = 1.0 / self.node_count
        old_page_rank = self.get_empty_mass()
        neighbors = node_data
    else:
        new_page_rank = node_data[0]
        old_page_rank = node_data[1]
        neighbors = node_data[2]

    return new_page_rank, old_page_rank, neighbors, None

"""
Return the mass as-is.
"""
def get_dangling_mass(self, page_rank, metadata):
    return page_rank
```

```python
    """
    This is a scalar, so just compute the direct difference.
    """
    def get_squared_rank_change(self, new_page_rank, old_page_rank):
        return (new_page_rank - old_page_rank) ** 2

    """
    Returns 0
    """
    def get_empty_mass(self):
        return 0.0

    """
    Sum the values together.
    """
    def get_merged_mass(self, old_mass, new_mass):
        return old_mass + new_mass

    """
    Yield the accumulated probability mass and squared rank change.
    """
    def mapper_final(self):
        yield 'dangling_mass', self.dangling_mass
        yield 'squared_rank_change', self.squared_rank_change

    """
    Combine the probability mass or the squared rank change.
    """
    def reducer(self, key, values):
        total_value = self.get_empty_mass()

        for value in values:
            total_value = self.get_merged_mass(total_value, value)

        yield key, total_value

    """
    Set the mapper and reducer count options to make sure that MRJob creates enough
    mapper/reducer tasks.
    """
    def steps(self):
        step = MRStep(
            mapper_init = self.mapper_init, mapper = self.mapper,
            mapper_final = self.mapper_final, reducer = self.reducer,
            jobconf = {
                'mapreduce.job.maps': self.options.mapper_count,
                'mapreduce.job.reduces': 2
            })

        return [step]

if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
    job = CheckPageRankConvergenceJob()
    job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def check_page_rank_convergence_job(
            python_file, runner_type, graph_file, load_only = False):

            if graph_file.find('input/') == 0:
                output_folder = 'output/' + graph_file[6:] + '.converge_summary'
            elif graph_file.find('output/') == 0:
                output_folder = graph_file + '.converge_summary'
            else:
                output_folder = 'output/' + graph_file + '.converge_summary'

            if not load_only or not folder_exists(runner_type, output_folder):
                remove_folder(runner_type, output_folder)

                mrjob_output_folder = get_mrjob_path(runner_type, output_folder)
                mrjob_graph_file = get_mrjob_path(runner_type, graph_file)

                !python $python_file \
                    -r $runner_type \
                    --strict-protocols \
                    --no-bootstrap-mrjob \
                    --no-output \
                    --file node_count.txt \
                    --mapper-count $mapper_count \
                    --output-dir $mrjob_output_folder \
                    $mrjob_graph_file \
                    2>> $debug_output

            # There are two lines in the output, and they summarize the result of the PageRank
            # iteration. Transform them into key-value pairs and return them as a dictionary.

            job_output = pipe_cat_output(runner_type, output_folder)

            convergence_summary = {}

            for line in job_output.strip().split('\n'):
                key, value = line.split('\t', 1)
                convergence_summary[eval(key)] = eval(value)

            return convergence_summary
```

3.3 Create PageRank driver

Next, provide a driver function which will run a specified number of iterations of the PageRank algorithm, starting from giving all nodes uniform weight, or until the PageRank algorithm converged.

```
In [ ]: def page_rank_driver(
            page_rank_python_file, check_converge_python_file, runner_type, graph_file,
            output_base_folder, damping_factor = 0.85, iteration_count = 100,
            converge_threshold = 0.001, show_progress = True, show_final_status = True,
            resume = False):

            # Prepare initial iteration
```

```python
iteration_id = 0
converged = False

if not resume:
    remove_folder(runner_type, output_base_folder)

next_graph_file = '%s/%03d' % (output_base_folder, 1)

while folder_exists(runner_type, next_graph_file):
    iteration_id += 1
    graph_file = next_graph_file
    next_graph_file = '%s/%03d' % (output_base_folder, iteration_id + 1)

# If we are resuming, check to see if we already converged

if show_progress:
    now = datetime.today()
    print now, 'Running convergence check for iteration', iteration_id

convergence_summary = check_page_rank_convergence_job(
    check_converge_python_file, runner_type, graph_file, True)

squared_rank_change = convergence_summary['squared_rank_change']

if isinstance(squared_rank_change, dict):
    rank_change = max(squared_rank_change.values()) ** 0.5
else:
    rank_change = squared_rank_change ** 0.5

dangling_mass = convergence_summary['dangling_mass']

if iteration_id != 0:
    converged = rank_change <= converge_threshold

# Iterate until convergence, or until the number of iterations have completed

while iteration_id < iteration_count and not converged:
    iteration_id += 1

    if show_progress:
        now = datetime.today()
        print now, 'Running PageRank iteration', iteration_id

    next_graph_file = '%s/%03d' % (output_base_folder, iteration_id)

    with open('dangling_mass.txt', 'w') as dangling_mass_file:
        json.dump(dangling_mass, dangling_mass_file)

    page_rank_single_iteration_job(
        page_rank_python_file, runner_type, graph_file, next_graph_file,
        damping_factor)

    if show_progress:
```

```
            now = datetime.today()
            print now, 'Running convergence check for iteration', iteration_id

        convergence_summary = check_page_rank_convergence_job(
            check_converge_python_file, runner_type, next_graph_file)

        squared_rank_change = convergence_summary['squared_rank_change']

        if isinstance(squared_rank_change, dict):
            rank_change = max(squared_rank_change.values()) ** 0.5
        else:
            rank_change = squared_rank_change ** 0.5

        converged = rank_change <= converge_threshold

        # Prepare for the next iteration

        dangling_mass = convergence_summary['dangling_mass']
        graph_file = next_graph_file

    if show_final_status:
        now = datetime.today()

        print

        if converged:
            print now, 'PageRank converged after', iteration_id, 'iterations'
        else:
            print now, 'PageRank did not converge after', iteration_id, 'iterations'
            print now, 'PageRank scores moved by', rank_change, 'in last iteration'

    # Return the path to the last graph file so that we can examine it.

    return graph_file
```

Now we use it for the regular PageRank algorithm.

```
In [ ]: run_page_rank = functools.partial(
            page_rank_driver, 'PageRankSingleIterationJob.py', 'CheckPageRankConvergenceJob.py')
```

3.4 Acquire PageRank test data

As you build your code, use the test data

- s3://ucb-mids-mls-networks/PageRank-test.txt (S3)
- https://www.dropbox.com/sh/2c0k5adwz36lkcw/AADxzBgNxNF5Q6-eanjnK64qa/PageRank-test.txt (Dropbox)

with teleportation parameter $(1 - d)$ set to 0.15 (where d, the damping factor is set to 0.85).

```
In [ ]: test_out = get_dropbox_file(
            '2c0k5adwz36lkcw/AADxzBgNxNF5Q6-eanjnK64qa', 'test', 'PageRank-test.txt')
```

It's easier to perform the page rank computation if we add all the dangling nodes to the graph.

```
In [ ]: test_all = add_dangling_nodes_job('inline', test_out, None)
```

3.5 Run PageRank on test data

As a convenience for this smaller test graph, provide a method which runs page rank and returns the results as a dictionary.

```
In [ ]: def get_page_ranks(
            runner_type, driver, graph_file, output_base_folder, damping_factor = 0.85,
            show_final_status = False, resume = False, iterations = 50):

            result_graph_file = driver(
                runner_type, graph_file, output_base_folder, damping_factor, iterations, 0.0001,
                False, show_final_status, resume)

            output = pipe_cat_output(runner_type, result_graph_file)

            graph = {}

            for line in output.split('\n'):
                key, result = line.split('\t', 1)

                name = eval(key)

                value = eval(result)
                page_rank = value[0]
                metadata = value[3]

                graph[name] = (page_rank, neighbors, metadata)

            return graph
```

First, we compute the number of dangling nodes.

```
In [ ]: test_out_node_count = get_line_count('inline', test_out)
        test_all_node_count = get_line_count('inline', test_all)

        with open('node_count.txt', 'w') as node_count_file:
            json.dump(test_all_node_count, node_count_file)
```

```
In [ ]: # Since we'll be calling this in the next question, create an alias for it.

        get_test_page_ranks = functools.partial(
            get_page_ranks, 'inline', run_page_rank, test_all, 'output/test')

        # Run PageRank and time how long it takes to converge on the small test graph.

        %time test_page_ranks = get_test_page_ranks(0.85, True)
```

```
2016-03-19 09:58:24.558821 PageRank converged after 50 iterations
CPU times: user 352 ms, sys: 998 ms, total: 1.35 s
Wall time: 37.5 s
```

3.6 Cross-check PageRank test data result

Crosscheck your work with the true result, displayed in the first image in the Wikipedia article:

https://en.wikipedia.org/wiki/PageRank

Here for reference are the corresponding PageRank probabilities:

```
A,0.033
B,0.384
C,0.343
D,0.039
E,0.081
F,0.039
G,0.016
H,0.016
I,0.016
J,0.016
K,0.016
```

In [ ]:
```
for name, value in sorted(test_page_ranks.items()):
    page_rank, neighbors, metadata = value
    print '%s,%0.3f' % (name, page_rank)
```

```
A,0.033
B,0.384
C,0.343
D,0.039
E,0.081
F,0.039
G,0.016
H,0.016
I,0.016
J,0.016
K,0.016
```

4 HW 9.2: Exploring PageRank teleportation and network plots

In order to overcome problems such as disconnected components, the damping factor (a typical value for d is 0.85) can be varied. Using the graph in HW9.1, plot the test graph (using networkx, https://networkx.github.io/) for several values of the damping factor, so that each nodes radius is proportional to its PageRank score.

4.1 Add utility to plot a PageRank graph

In [ ]:
```
def plot_page_rank(subplot, title, page_ranks):

    # Build up edges and create a graph

    graph = networkx.MultiDiGraph()

    for name, value in page_ranks.iteritems():
        page_rank, neighbors, metadata = value
        graph.add_edges_from([
            (name, neighbor_name) for neighbor_name in neighbors.iterkeys()
                if neighbor_name in page_ranks
        ])

    # Compute node sizes and labels based on page rank values. Use square roots of the
    # page rank as the radius scale factor to avoid being misleading about area.
```

```
    node_sizes = [
        (page_ranks[node_id][0] ** 0.5) * 10000
            for node_id in graph.nodes()
    ]

    # Create a circular layout for consistency unless we have too many nodes for the
    # circle to make sense.

    if len(node_sizes) <= 20:
        node_labels = {
            node_id: node_id + '\n' + ('%0.01f' % (page_ranks[node_id][0] * 100)) + '%'
                for node_id in graph.nodes()
        }

        node_positions = networkx.circular_layout(graph)
    else:
        node_labels = { node_id: '' for node_id in graph.nodes() }

        node_positions = networkx.fruchterman_reingold_layout(graph)

    # Plot the graph

    networkx.draw_networkx(
        graph,
        ax = subplot,
        style = 'dotted',
        arrows = False,
        node_color = '0.9',
        pos = node_positions,
        node_size = node_sizes,
        labels = node_labels)

    subplot.axis('off')
    subplot.set_title(title)
```

4.2 Run PageRank with various damping factors

In particular you should do this for the following damping factors: [0,0.25,0.5,0.75, 0.85, 1].

First, we'll compute the resulting page rank weights.

```
In [ ]: damping_factors = [0.0, 0.25, 0.5, 0.75, 0.85, 1.0]

        graphs = {
            damping_factor: get_test_page_ranks(damping_factor)
                for damping_factor in damping_factors
        }
```

4.3 Plot networkx graph for various damping factors

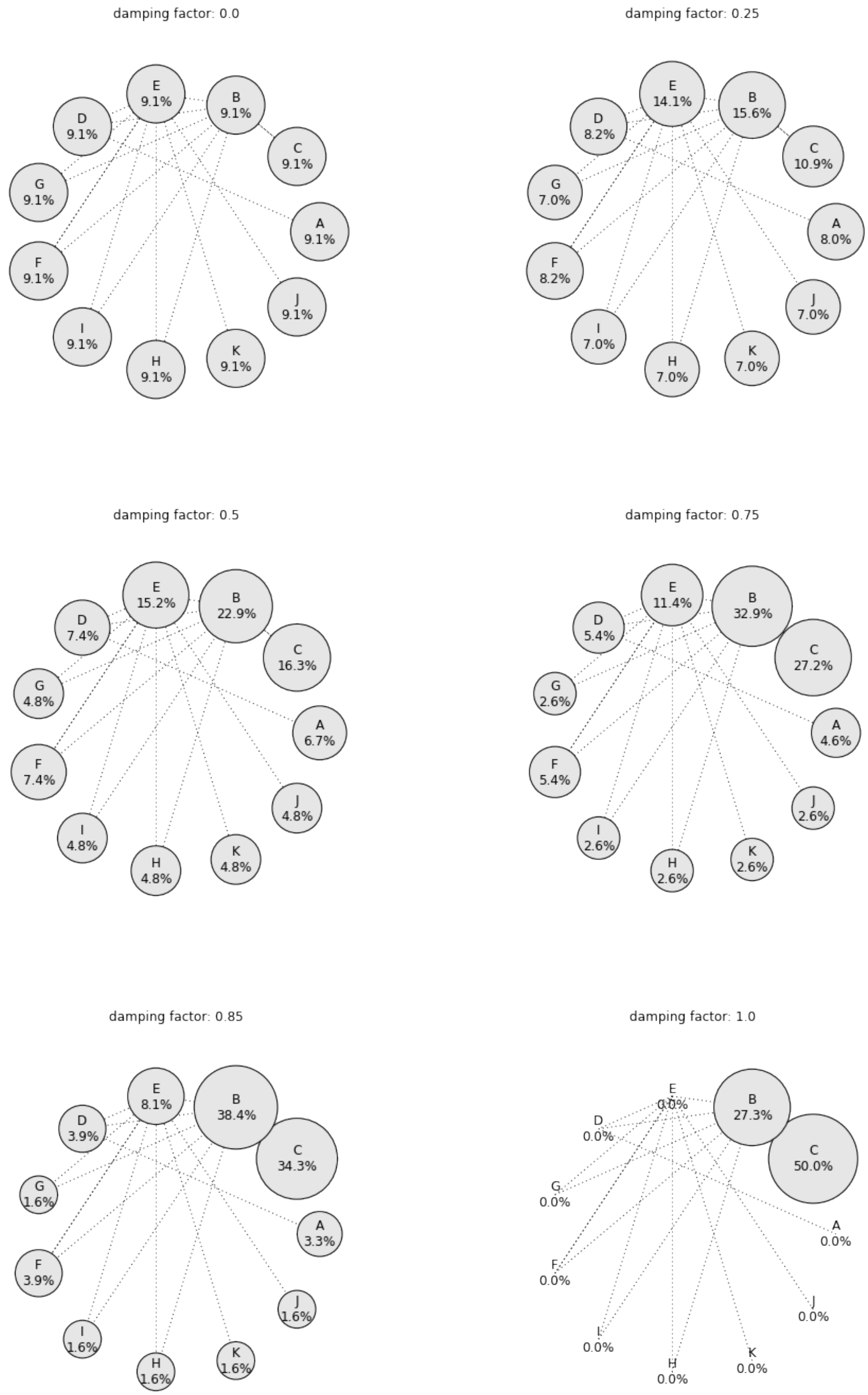
With that, we can plot the graphs.

```
In [ ]: graph_id = 0
```

```
grid_cols = 2
grid_rows = math.ceil(len(damping_factors) / grid_cols)

fig = matplotlib.pyplot.figure(figsize = (16, 8 * grid_rows))

for damping_factor, page_ranks in sorted(graphs.iteritems()):
    graph_id += 1
    subplot = fig.add_subplot(grid_rows, grid_cols, graph_id)
    plot_page_rank(subplot, 'damping factor: ' + str(damping_factor), page_ranks)
```


damping factor: 0.0
E 9.1%
B 9.1%
D 9.1%
C 9.1%
G 9.1%
A 9.1%
F 9.1%
J 9.1%
I 9.1%
H 9.1%
K 9.1%
damping factor: 0.25
E 14.1%
B 15.6%
D 8.2%
C 10.9%
G 7.0%
A 8.0%
F 8.2%
J 7.0%
I 7.0%
H 7.0%
K 7.0%
damping factor: 0.5
E 15.2%
B 22.9%
D 7.4%
C 16.3%
G 4.8%
A 6.7%
F 7.4%
J 4.8%
I 4.8%
H 4.8%
K 4.8%
damping factor: 0.75
E 11.4%
B 32.9%
D 5.4%
C 27.2%
G 2.6%
A 4.6%
F 5.4%
J 2.6%
I 2.6%
H 2.6%
K 2.6%
damping factor: 0.85
E 8.1%
B 38.4%
D 3.9%
C 34.3%
G 1.6%
A 3.3%
F 3.9%
J 1.6%
I 1.6%
H 1.6%
K 1.6%
damping factor: 1.0
E 0.0%
B 27.3%
D 0.0%
C 50.0%
G 0.0%
A 0.0%
F 0.0%
J 0.0%
I 0.0%
H 0.0%
K 0.0%

5 HW 9.3: Applying PageRank to the Wikipedia hyperlinks network

5.1 Acquire Wikipedia hyperlinks network

We will need both the `-out` and the `-in` degree node files.

```
In [ ]: wikipedia_out = get_s3_file('wikipedia', 'all-pages-indexed-out.txt')
        wikipedia_in = get_s3_file('wikipedia', 'all-pages-indexed-in.txt')
        wikipedia_indices = get_s3_file('wikipedia', 'indices.txt')
```

Split the files so that Hadoop knows to create enough mapper tasks.

```
In [ ]: split_for_hdfs(wikipedia_out)
        split_for_hdfs(wikipedia_in)
        split_for_hdfs(wikipedia_indices)
```

It's easier to perform the page rank computation if we add all the dangling nodes to the graph.

```
In [ ]: %time wikipedia_all = add_dangling_nodes_job('hadoop', wikipedia_out, wikipedia_in)
```

```
CPU times: user 8.5 s, sys: 1.13 s, total: 9.62 s
Wall time: 10min 37s
```

5.2 Create job to sort by PageRank

```
In [ ]: import heapq
        import math
        from mrjob.job import MRJob
        from mrjob.step import MRStep
        from mrjob.protocol import ReprProtocol
        import sys

        class PageRankTopNJob(MRJob):

            INPUT_PROTOCOL = ReprProtocol
            INTERNAL_PROTOCOL = ReprProtocol
            OUTPUT_PROTOCOL = ReprProtocol

            """
            Allow configuration of the N used for the top-N job.
            """
            def configure_options(self):
                super(PageRankTopNJob, self).configure_options()
                self.add_passthrough_option('--n', default=100, type='int')
                self.add_passthrough_option('--mapper-count', default=1, type='int')

            """
            Initialize our priority queue to an empty list.
            """
            def mapper_init(self):
                self.top_n = []

            """
            Buffer the top N results on the mapper side so that we can emit them during the final
```

```
    stage to reduce the amount of network traffic. Allows single reducer approach to work
    for larger networks like the Wikipedia graph.
    """
    def mapper(self, key, node_data):
        old_page_rank = node_data[0]

        # Use log page rank in case we decide to switch over to Hadoop sort rather
        # than an in-memory sort for the reducer.

        log_page_rank = math.log(old_page_rank)
        heap_value = (log_page_rank, key) + node_data

        if len(self.top_n) == self.options.n:
            heapq.heappushpop(self.top_n, heap_value)
        else:
            heapq.heappush(self.top_n, heap_value)

    """
    Emit each of the items to the None key so that we can perform a reducer-side sort.
    """
    def mapper_final(self):
        for item in self.top_n:
            yield None, item

    """
    Reducer which accumulates the top N and then emits them.
    """
    def reducer(self, _, all_items):
        top_n = []

        for item in all_items:
            if len(top_n) == self.options.n:
                heapq.heappushpop(top_n, item)
            else:
                heapq.heappush(top_n, item)

        for item in heapq.nlargest(self.options.n, top_n):
            key = item[1]
            node_data = item[2:]

            yield key, node_data

    """
    Set the mapper and reducer count options to make sure that MRJob creates enough
    mapper/reducer tasks.
    """
    def steps(self):
        step = MRStep(
            mapper_init = self.mapper_init, mapper = self.mapper,
            mapper_final = self.mapper_final, reducer = self.reducer,
            jobconf = {
                'mapreduce.job.maps': self.options.mapper_count,
                'mapreduce.job.reduces': 1
            })
```

```
        return [step]

if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
    job = PageRankTopNJob()
    job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def page_rank_top_n_job(runner_type, graph_file, n, reducer_count = 1):
            output_folder = graph_file + '.top' + str(n)

            remove_folder(runner_type, output_folder)

            mrjob_graph_file = get_mrjob_path(runner_type, graph_file)
            mrjob_output_folder = get_mrjob_path(runner_type, output_folder)

            !python PageRankTopNJob.py \
                -r $runner_type \
                --strict-protocols \
                --no-bootstrap-mrjob \
                --no-output \
                --n $n \
                --mapper-count $mapper_count \
                --reducer-count $reducer_count \
                --output-dir $mrjob_output_folder \
                $mrjob_graph_file \
                2>> $debug_output

            output = pipe_cat_output(runner_type, output_folder)

            topn_graph = {}

            for line in output.split('\n'):
                key, result = line.split('\t', 1)

                name = eval(key)

                value = eval(result)
                page_rank = value[0]
                neighbors = value[2]

                topn_graph[name] = (page_rank, neighbors)

            return topn_graph
```

Also provide a utility function that can print it in a nice table.

```
In [ ]: """
        Prints the nodes in the page rank graph by joining on the given indices file. Essentially
        this is a hash join but done outside of MapReduce.
        """
        def get_page_rank_table(page_rank_graph):
            node_names = {}
```

```
    with open('input/wikipedia/indices.txt') as indices_file:
        for line in indices_file:
            node_name, node_id, rest = line.split('\t', 2)

            if node_id in page_rank_graph:
                node_names[node_id] = node_name

    page_rank_list = [
        (key, node_names[key], value[0])
            for key, value in page_rank_graph.iteritems()
    ]

    sorted_page_rank_list = sorted(page_rank_list, key = lambda x: x[2], reverse = True)

    return pandas.DataFrame(
        sorted_page_rank_list,
        columns = ['NodeId', 'NodeName', 'PageRank'])
```

5.3 Prepare Wikipedia for PageRank

First, we compute the number of dangling nodes.

```
In [ ]: wikipedia_out_node_count = get_line_count('hadoop', wikipedia_out)
        wikipedia_all_node_count = get_line_count('hadoop', wikipedia_all)

        with open('node_count.txt', 'w') as node_count_file:
            json.dump(wikipedia_all_node_count, node_count_file)
```

Then, we create a utility function which will run PageRank on the Wikipedia data set using the Hadoop runner.

```
In [ ]: run_wikipedia_page_ranks = functools.partial(
            run_page_rank, 'hadoop', wikipedia_all, 'output/wikipedia', 0.85)
```

5.4 Check PageRank after 5 iterations

Run your PageRank implementation on the Wikipedia dataset for 5 iterations.

s3://ucb-mids-mls-networks/wikipedia/

Display the top 100 ranked nodes with $d = 0.85$, corresponding to teleportation factor $(1 - d) = 0.15$.

5.4.1 Run PageRank for 5 iterations

```
In [ ]: %time unsorted_wikipedia_page_ranks_05 = \
            run_wikipedia_page_ranks(5, 0, True, False, True)
```

```
2016-03-15 06:35:52.298975 Running PageRank iteration 3
2016-03-15 07:00:15.229310 Running convergence check for iteration 3
2016-03-15 07:04:51.012614 Running PageRank iteration 4
2016-03-15 07:27:51.682574 Running convergence check for iteration 4
2016-03-15 07:31:57.421949 Running PageRank iteration 5
2016-03-15 07:55:59.715481 Running convergence check for iteration 5
CPU times: user 1min 10s, sys: 11.8 s, total: 1min 22s
Wall time: 1h 25min 4s
```

5.4.2 Check top 100 after 5 iterations

In [ ]:
```
%time top100_wikipedia_page_ranks_05 = \
    page_rank_top_n_job('hadoop', unsorted_wikipedia_page_ranks_05, 100)
```

```
Deleted /user/ubuntu/output/wikipedia/005.top100
CPU times: user 2.35 s, sys: 167 ms, total: 2.52 s
Wall time: 2min 37s
```

In [ ]:
```
wikipedia_df_05 = get_page_rank_table(top100_wikipedia_page_ranks_05)
wikipedia_df_05.to_csv('top100_wikipedia_page_ranks_05.csv')
wikipedia_df_05
```

Out[ ]:

	NodeId	NodeName	PageRank
0	13455888	United States	0.0015
1	1184351	Animal	0.0007
2	4695850	France	0.0006
3	5051368	Germany	0.0006
4	1384888	Arthropod	0.0005
5	7902219	List of sovereign states	0.0005
6	6113490	Insect	0.0005
7	2437837	Canada	0.0004
8	6076759	India	0.0004
9	13425865	United Kingdom	0.0004
10	4196067	England	0.0004
11	6172466	Iran	0.0004
12	14112583	World War II	0.0004
13	10390714	Poland	0.0004
14	15164193	village	0.0004
15	3191491	Countries of the world	0.0003
16	7835160	List of countries	0.0003
17	6416278	Japan	0.0003
18	6237129	Italy	0.0003
19	1516699	Australia	0.0003
20	13725487	Voivodeships of Poland	0.0003
21	7576704	Lepidoptera	0.0003
22	9276255	National Register of Historic Places	0.0003
23	10469541	Powiat	0.0003
24	5154210	Gmina	0.0003
25	7990491	London	0.0003
26	12836211	The New York Times	0.0003
27	4198751	English language	0.0003
28	2797855	China	0.0003
29	11253108	Russia	0.0003
30	3603527	Departments of France	0.0003
31	3069099	Communes of France	0.0003
32	9386580	New York City	0.0003
33	12074312	Spain	0.0003
34	14881689	moth	0.0003
35	2155467	Brazil	0.0002
36	1441065	Association football	0.0002
37	14503460	association football	0.0002
38	3191268	Counties of Iran	0.0002
39	10566120	Provinces of Iran	0.0002
40	2396749	California	0.0002

41	11147327	Romania	0.0002
42	2614581	Central European Time	0.0002
43	1637982	Bakhsh	0.0002
44	11245362	Rural Districts of Iran	0.0002
45	12430985	Sweden	0.0002
46	9355455	Netherlands	0.0002
47	10527224	Private Use Areas	0.0002
48	6172167	Iran Standard Time	0.0002
49	2614578	Central European Summer Time	0.0002
50	981395	AllMusic	0.0002
51	14112408	World War I	0.0002
52	8697871	Mexico	0.0002
53	9391762	New York	0.0002
54	6171937	Iran Daylight Time	0.0002
55	5490435	Hangul	0.0002
56	14725161	gene	0.0002
57	11582765	Scotland	0.0002
58	9562547	Norway	0.0002
59	994890	Allmusic	0.0002
60	12067030	Soviet Union	0.0002
61	10345830	Plant	0.0002
62	9394907	New Zealand	0.0002
63	13280859	Turkey	0.0002
64	9997298	Paris	0.0002
65	4978429	Geographic Names Information System	0.0002
66	12447593	Switzerland	0.0002
67	8019937	Los Angeles	0.0002
68	11148415	Romanize	0.0002
69	13432150	United States Census Bureau	0.0001
70	4344962	Europe	0.0001
71	1175360	Angiosperms	0.0001
72	4624519	Flowering plant	0.0001
73	12038331	South Africa	0.0001
74	14565507	census	0.0001
75	14981725	protein	0.0001
76	1523975	Austria	0.0001
77	13328060	U.S. state	0.0001
78	2826544	Chordate	0.0001
79	10399499	Political divisions of the United States	0.0001
80	1332806	Argentina	0.0001
81	14963657	population density	0.0001
82	1813634	Belgium	0.0001
83	2578813	Catholic Church	0.0001
84	1575979	BBC	0.0001
85	2778099	Chicago	0.0001
86	9924814	Pakistan	0.0001
87	13853369	Washington, D.C.	0.0001
88	4568647	Finland	0.0001
89	14727077	genus	0.0001
90	3328327	Czech Republic	0.0001
91	15070394	species	0.0001
92	3973000	Eastern European Time	0.0001
93	9742161	Ontario	0.0001
94	14709489	football (soccer)	0.0001

```
95   10246542                                 Philippines    0.0001
96    3591832                                     Denmark    0.0001
97    4320007                                    Eudicots    0.0001
98    5908108                                     Hungary    0.0001
99    5274313                                      Greece    0.0001
```

5.5 Check PageRank after 10 iterations

Run your PageRank implementation on the Wikipedia dataset for 10 iterations, and display the top 100 ranked nodes with $d = 0.85$, corresponding to teleportation factor $(1 - d) = 0.15$.

5.5.1 Run PageRank for 10 iterations

```
In [ ]: %time unsorted_wikipedia_page_ranks_10 = \
            run_wikipedia_page_ranks(10, 0, True, False, True)
```

```
2016-03-15 08:19:25.593177 Running PageRank iteration 6
2016-03-15 08:37:10.350500 Running convergence check for iteration 6
2016-03-15 08:40:24.715343 Running PageRank iteration 7
2016-03-15 08:57:09.767643 Running convergence check for iteration 7
2016-03-15 09:00:46.333433 Running PageRank iteration 8
2016-03-15 09:18:32.381305 Running convergence check for iteration 8
2016-03-15 09:22:03.980942 Running PageRank iteration 9
2016-03-15 09:39:52.245350 Running convergence check for iteration 9
2016-03-15 09:43:28.774334 Running PageRank iteration 10
2016-03-15 10:00:14.413423 Running convergence check for iteration 10
CPU times: user 1min 28s, sys: 10.9 s, total: 1min 39s
Wall time: 1h 44min 32s
```

5.5.2 Check top 100 after 5 iterations

```
In [ ]: %time top100_wikipedia_page_ranks_10 = \
            page_rank_top_n_job('hadoop', unsorted_wikipedia_page_ranks_10, 100)
```

```
CPU times: user 2.18 s, sys: 395 ms, total: 2.58 s
Wall time: 2min 23s
```

```
In [ ]: wikipedia_df_10 = get_page_rank_table(top100_wikipedia_page_ranks_10)
        wikipedia_df_10.to_csv('top100_wikipedia_page_ranks_10.csv')
        wikipedia_df_10
```

```
Out[ ]:       NodeId                                 NodeName  PageRank
        0   13455888                            United States    0.0015
        1    1184351                                   Animal    0.0007
        2    4695850                                   France    0.0006
        3    5051368                                  Germany    0.0006
        4    1384888                                Arthropod    0.0005
        5    2437837                                   Canada    0.0004
        6    6113490                                   Insect    0.0004
        7    7902219                 List of sovereign states    0.0004
        8   13425865                           United Kingdom    0.0004
        9    6076759                                    India    0.0004
        10   4196067                                  England    0.0004
        11   6172466                                     Iran    0.0004
        12  14112583                             World War II    0.0004
        13  10390714                                   Poland    0.0004
```

14	15164193	village	0.0003
15	3191491	Countries of the world	0.0003
16	6416278	Japan	0.0003
17	6237129	Italy	0.0003
18	7835160	List of countries	0.0003
19	1516699	Australia	0.0003
20	13725487	Voivodeships of Poland	0.0003
21	9276255	National Register of Historic Places	0.0003
22	7576704	Lepidoptera	0.0003
23	10469541	Powiat	0.0003
24	5154210	Gmina	0.0003
25	12836211	The New York Times	0.0003
26	7990491	London	0.0003
27	4198751	English language	0.0003
28	2797855	China	0.0003
29	11253108	Russia	0.0003
30	9386580	New York City	0.0003
31	3603527	Departments of France	0.0003
32	12074312	Spain	0.0003
33	3069099	Communes of France	0.0002
34	14881689	moth	0.0002
35	2155467	Brazil	0.0002
36	1441065	Association football	0.0002
37	14503460	association football	0.0002
38	2396749	California	0.0002
39	3191268	Counties of Iran	0.0002
40	10566120	Provinces of Iran	0.0002
41	2614581	Central European Time	0.0002
42	11147327	Romania	0.0002
43	1637982	Bakhsh	0.0002
44	12430985	Sweden	0.0002
45	11245362	Rural Districts of Iran	0.0002
46	9355455	Netherlands	0.0002
47	10527224	Private Use Areas	0.0002
48	14112408	World War I	0.0002
49	2614578	Central European Summer Time	0.0002
50	9391762	New York	0.0002
51	8697871	Mexico	0.0002
52	6172167	Iran Standard Time	0.0002
53	981395	AllMusic	0.0002
54	6171937	Iran Daylight Time	0.0002
55	5490435	Hangul	0.0002
56	11582765	Scotland	0.0002
57	14725161	gene	0.0002
58	12067030	Soviet Union	0.0002
59	9562547	Norway	0.0002
60	994890	Allmusic	0.0002
61	9997298	Paris	0.0002
62	9394907	New Zealand	0.0002
63	13280859	Turkey	0.0002
64	10345830	Plant	0.0002
65	4978429	Geographic Names Information System	0.0002
66	12447593	Switzerland	0.0002
67	8019937	Los Angeles	0.0002

68	11148415	Romanize	0.0001
69	13432150	United States Census Bureau	0.0001
70	4344962	Europe	0.0001
71	1175360	Angiosperms	0.0001
72	12038331	South Africa	0.0001
73	14565507	census	0.0001
74	4624519	Flowering plant	0.0001
75	1523975	Austria	0.0001
76	14981725	protein	0.0001
77	13328060	U.S. state	0.0001
78	1332806	Argentina	0.0001
79	10399499	Political divisions of the United States	0.0001
80	14963657	population density	0.0001
81	2578813	Catholic Church	0.0001
82	2826544	Chordate	0.0001
83	1575979	BBC	0.0001
84	1813634	Belgium	0.0001
85	2778099	Chicago	0.0001
86	13853369	Washington, D.C.	0.0001
87	9924814	Pakistan	0.0001
88	4568647	Finland	0.0001
89	12785678	The Guardian	0.0001
90	7467127	Latin	0.0001
91	9742161	Ontario	0.0001
92	3328327	Czech Republic	0.0001
93	10246542	Philippines	0.0001
94	3591832	Denmark	0.0001
95	5274313	Greece	0.0001
96	14727077	genus	0.0001
97	14709489	football (soccer)	0.0001
98	5908108	Hungary	0.0001
99	3973000	Eastern European Time	0.0001

5.6 Compare top 100 for different iterations

Have the top 100 ranked pages changed? Comment on your findings.

5.6.1 Overlap check

Find the set intersection to check for the number of nodes that overlap.

```
In [ ]: top100_nodes_05 = set(top100_wikipedia_page_ranks_05.keys())
        top100_nodes_10 = set(top100_wikipedia_page_ranks_10.keys())

        intersection = top100_nodes_05 & top100_nodes_10
        print 'intersection:', len(intersection), 'nodes'
```

```
intersection: 98 nodes
```

From the size of the intersection, we can see that the top 100 are consistently the same pages after the first 10 iterations (there is a 98% overlap) and that any position changes in the top 100 are probably switches between the pages.

5.6.2 Distance check

We can also check the Levenshtein distance between the two rankings to see how much the rankings themselves have changed.

In [ ]:
```
# Borrowed under Creative Commons
# http://hetland.org/coding/python/levenshtein.py

def levenshtein(a,b):
    "Calculates the Levenshtein distance between a and b."
    n, m = len(a), len(b)
    if n > m:
        # Make sure n <= m, to use O(min(n,m)) space
        a,b = b,a
        n,m = m,n

    current = range(n+1)
    for i in range(1,m+1):
        previous, current = current, [i]+[0]*n
        for j in range(1,n+1):
            add, delete = previous[j]+1, current[j-1]+1
            change = previous[j-1]
            if a[j-1] != b[i-1]:
                change = change + 1
            current[j] = min(add, delete, change)

    return current[n]

levenshtein(wikipedia_df_05['NodeId'].tolist(), wikipedia_df_10['NodeId'].tolist())
```

Out[ ]: 48

The Levenshtein distance is 48, indicating that the similarity between the two rankings is only 52%. Therefore, while there is substantial overlap, the two are not as similar as the overlap suggests. Namely, while the top 100 has been more or less established, between the fifth iterations and the tenth iteration, there have been rank switches.

5.7 Plot PageRank of top 100 ranked pages

> Plot the pagerank values for the top 100 pages resulting from the 5 iterations run. Then plot the pagerank values for the same 100 pages that resulted from the 10 iterations run.

While we could create a MapReduce job to retrieve the new value of the top 100 pages, we know from the previous analysis of the overlaps that we're actually only missing two values, and checking the merged result tables, they are both very low rank (species at rank 91 and Eudicots at rank 97).

In [ ]:
```
wikipedia_df_05 = pandas.DataFrame.from_csv('top100_wikipedia_page_ranks_05.csv')
wikipedia_df_10 = pandas.DataFrame.from_csv('top100_wikipedia_page_ranks_10.csv')

wikipedia_compare_df = pandas.merge(
    wikipedia_df_05[['NodeName', 'PageRank']],
    wikipedia_df_10[['NodeName', 'PageRank']],
    on = ['NodeName'], how = 'left')

wikipedia_compare_df.columns = [
    'NodeName', 'PageRank after 5 Iterations', 'PageRank after 10 Iterations'
]

wikipedia_compare_df
```

Out[ ]:

	NodeName	PageRank after 5 Iterations	\
0	United States	0.0015	
1	Animal	0.0007	
2	France	0.0006	
3	Germany	0.0006	
4	Arthropod	0.0005	
5	List of sovereign states	0.0005	
6	Insect	0.0005	
7	Canada	0.0004	
8	India	0.0004	
9	United Kingdom	0.0004	
10	England	0.0004	
11	Iran	0.0004	
12	World War II	0.0004	
13	Poland	0.0004	
14	village	0.0004	
15	Countries of the world	0.0003	
16	List of countries	0.0003	
17	Japan	0.0003	
18	Italy	0.0003	
19	Australia	0.0003	
20	Voivodeships of Poland	0.0003	
21	Lepidoptera	0.0003	
22	National Register of Historic Places	0.0003	
23	Powiat	0.0003	
24	Gmina	0.0003	
25	London	0.0003	
26	The New York Times	0.0003	
27	English language	0.0003	
28	China	0.0003	
29	Russia	0.0003	
30	Departments of France	0.0003	
31	Communes of France	0.0003	
32	New York City	0.0003	
33	Spain	0.0003	
34	moth	0.0003	
35	Brazil	0.0002	
36	Association football	0.0002	
37	association football	0.0002	
38	Counties of Iran	0.0002	
39	Provinces of Iran	0.0002	
40	California	0.0002	
41	Romania	0.0002	
42	Central European Time	0.0002	
43	Bakhsh	0.0002	
44	Rural Districts of Iran	0.0002	
45	Sweden	0.0002	
46	Netherlands	0.0002	
47	Private Use Areas	0.0002	
48	Iran Standard Time	0.0002	
49	Central European Summer Time	0.0002	
50	AllMusic	0.0002	
51	World War I	0.0002	
52	Mexico	0.0002	

53	New York	0.0002
54	Iran Daylight Time	0.0002
55	Hangul	0.0002
56	gene	0.0002
57	Scotland	0.0002
58	Norway	0.0002
59	Allmusic	0.0002
60	Soviet Union	0.0002
61	Plant	0.0002
62	New Zealand	0.0002
63	Turkey	0.0002
64	Paris	0.0002
65	Geographic Names Information System	0.0002
66	Switzerland	0.0002
67	Los Angeles	0.0002
68	Romanize	0.0002
69	United States Census Bureau	0.0001
70	Europe	0.0001
71	Angiosperms	0.0001
72	Flowering plant	0.0001
73	South Africa	0.0001
74	census	0.0001
75	protein	0.0001
76	Austria	0.0001
77	U.S. state	0.0001
78	Chordate	0.0001
79	Political divisions of the United States	0.0001
80	Argentina	0.0001
81	population density	0.0001
82	Belgium	0.0001
83	Catholic Church	0.0001
84	BBC	0.0001
85	Chicago	0.0001
86	Pakistan	0.0001
87	Washington, D.C.	0.0001
88	Finland	0.0001
89	genus	0.0001
90	Czech Republic	0.0001
91	species	0.0001
92	Eastern European Time	0.0001
93	Ontario	0.0001
94	football (soccer)	0.0001
95	Philippines	0.0001
96	Denmark	0.0001
97	Eudicots	0.0001
98	Hungary	0.0001
99	Greece	0.0001

	PageRank after 10 Iterations
0	0.0015
1	0.0007
2	0.0006
3	0.0006
4	0.0005

5	0.0004
6	0.0004
7	0.0004
8	0.0004
9	0.0004
10	0.0004
11	0.0004
12	0.0004
13	0.0004
14	0.0003
15	0.0003
16	0.0003
17	0.0003
18	0.0003
19	0.0003
20	0.0003
21	0.0003
22	0.0003
23	0.0003
24	0.0003
25	0.0003
26	0.0003
27	0.0003
28	0.0003
29	0.0003
30	0.0003
31	0.0002
32	0.0003
33	0.0003
34	0.0002
35	0.0002
36	0.0002
37	0.0002
38	0.0002
39	0.0002
40	0.0002
41	0.0002
42	0.0002
43	0.0002
44	0.0002
45	0.0002
46	0.0002
47	0.0002
48	0.0002
49	0.0002
50	0.0002
51	0.0002
52	0.0002
53	0.0002
54	0.0002
55	0.0002
56	0.0002
57	0.0002
58	0.0002

```
59                          0.0002
60                          0.0002
61                          0.0002
62                          0.0002
63                          0.0002
64                          0.0002
65                          0.0002
66                          0.0002
67                          0.0002
68                          0.0001
69                          0.0001
70                          0.0001
71                          0.0001
72                          0.0001
73                          0.0001
74                          0.0001
75                          0.0001
76                          0.0001
77                          0.0001
78                          0.0001
79                          0.0001
80                          0.0001
81                          0.0001
82                          0.0001
83                          0.0001
84                          0.0001
85                          0.0001
86                          0.0001
87                          0.0001
88                          0.0001
89                          0.0001
90                          0.0001
91                             NaN
92                          0.0001
93                          0.0001
94                          0.0001
95                          0.0001
96                          0.0001
97                             NaN
98                          0.0001
99                          0.0001
```

With the values all grouped together in a table, we can compare the plotted raw values for the page ranks.

In [ ]:
```
plot_count = 4

figure, subplots = matplotlib.pyplot.subplots(
    plot_count, figsize = (16, 4 * plot_count), sharex = False, sharey = True)

for i in range(plot_count):
    start = int(i * 100 / plot_count)
    end = int((i + 1) * 100 / plot_count)

    wikipedia_compare_df[start:end].plot(
```

```
        ax = subplots[i], kind = 'bar', color=['#9C0046', '#87ceeb'])

    subplots[i].title.set_position((0.5,0.75))

    subplots[i].set_title(
        'Top %d-%d PageRank Scores\nAfter 5 and 10 Iterations' % (start + 1, end))

    subplots[i].set_xlabel('Top 100 Position after 5 Iterations')
    subplots[i].set_ylabel('PageRank Score (log scale)')
```

6 HW 9.4: Topic-specific PageRank implementation using MR-Job

6.1 Add topics to graph

6.1.1 Create MRJob to count topic occurrences

Unlike regular PageRank, topic-specific page rank needs separate counts for each topic in order to handle the dangling mass, so we'll create a job for it.

In [ ]:
```
from collections import defaultdict
from mrjob.job import MRJob
from mrjob.step import MRStep
from mrjob.protocol import ReprProtocol
import sys

class TopicOccurrenceCountJob(MRJob):

    INPUT_PROTOCOL = ReprProtocol
    INTERNAL_PROTOCOL = ReprProtocol
    OUTPUT_PROTOCOL = ReprProtocol

    def configure_options(self):
        super(TopicOccurrenceCountJob, self).configure_options()

        self.add_passthrough_option('--mapper-count', type='int', default=1)
        self.add_passthrough_option('--reducer-count', type='int', default=1)

    """
    Initialize all topic counts to zero.
    """
    def mapper_init(self):
        self.topic_counts = defaultdict(int)

    """
    Accumulate the topic counts within a mapper.
    """
    def mapper(self, name, topic):
        self.topic_counts[topic] += 1

    """
    Yield the accumulated topic counts.
    """
    def mapper_final(self):
        for topic, count in self.topic_counts.iteritems():
            yield topic, count

    """
    Sum the accumulated topic counts.
    """
    def reducer(self, topic, counts):
        yield topic, sum(counts)

    """
    Set the mapper and reducer count options to make sure that MRJob creates enough
```

```
        mapper/reducer tasks.
        """
        def steps(self):
            step = MRStep(
                mapper_init = self.mapper_init, mapper = self.mapper,
                mapper_final = self.mapper_final, reducer = self.reducer,
                jobconf = {
                    'mapreduce.job.maps': self.options.mapper_count,
                    'mapreduce.job.reduces': self.options.reducer_count
                })

            return [step]

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = TopicOccurrenceCountJob()
        job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def topic_occurrence_type_job(runner_type, topic_file, rerun = False):
            if topic_file is None:
                return None

            count_file = topic_file + '.counts'

            if not folder_exists(runner_type, count_file):
                remove_folder(runner_type, count_file)

                mrjob_topic_file = get_mrjob_path(runner_type, topic_file)
                mrjob_count_file = get_mrjob_path(runner_type, count_file)

                !python TopicOccurrenceCountJob.py \
                    -r $runner_type \
                    --strict-protocols \
                    --no-bootstrap-mrjob \
                    --no-output \
                    --output-dir $mrjob_count_file \
                    --mapper-count $mapper_count \
                    --reducer-count $reducer_count \
                    $mrjob_topic_file \
                    2>> $debug_output

            # Gather everything into a dictionary

            job_output = pipe_cat_output(runner_type, count_file)

            topic_counts = {}

            for line in job_output.split('\n'):
                topic, count_string = line.split('\t')
                topic_counts[eval(topic)] = int(count_string)

            return topic_counts
```

6.1.2 Create MRJob to add node topics to graph

In essence, we are performing a join on the two tables, with one containing the topic identifier and the other containing the neighbors. Therefore, we can create a job which will do that.

In [ ]:
```
from mrjob.job import MRJob
from mrjob.step import MRStep
from mrjob.protocol import ReprProtocol
import sys

class TagNodeWithTopicJob(MRJob):

    INPUT_PROTOCOL = ReprProtocol
    INTERNAL_PROTOCOL = ReprProtocol
    OUTPUT_PROTOCOL = ReprProtocol

    def configure_options(self):
        super(TagNodeWithTopicJob, self).configure_options()

        self.add_passthrough_option('--mapper-count', type='int', default=1)
        self.add_passthrough_option('--reducer-count', type='int', default=1)

    """
    We can identify whether it is the topic table or the graph table based on whether the
    input is a dictionary or a string/numeric value.
    """
    def mapper(self, name, value):
        if isinstance(value, dict):
            yield str(name), (value, None)
        else:
            topic = str(value)
            yield str(name), (None, topic)

    """
    Emit the left table row if found, and emit the blank entry if only right table entries
    were found (dangling node).
    """
    def reducer(self, name, all_data_rows):
        emit_left_data = None
        emit_right_data = None

        for data_row in all_data_rows:
            left_data, right_data = data_row

            if left_data is not None:
                emit_left_data = left_data
            if right_data is not None:
                emit_right_data = right_data

        yield name, (emit_left_data, emit_right_data)

    """
    Configure the reducer as a combiner and set the mapper and reducer count options to
    make sure that MRJob creates enough mapper/reducer tasks.
    """
```

```
        def steps(self):
            step = MRStep(
                mapper = self.mapper, combiner = self.reducer, reducer = self.reducer,
                jobconf = {
                    'mapreduce.job.maps': self.options.mapper_count,
                    'mapreduce.job.reduces': self.options.reducer_count,
                    'mapreduce.map.output.compress': 'true',
                    'mapred.map.output.compress.codec': \
                        'org.apache.hadoop.io.compress.SnappyCodec'
                })

            return [step]

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = TagNodeWithTopicJob()
        job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def tag_node_with_topic_job(runner_type, graph_file, topic_file):
            if graph_file is None or topic_file is None:
                return None

            output_folder = graph_file + '.topic_tagged'

            remove_folder(runner_type, output_folder)

            mrjob_graph_file = get_mrjob_path(runner_type, graph_file)
            mrjob_topic_file = get_mrjob_path(runner_type, topic_file)
            mrjob_output_folder = get_mrjob_path(runner_type, output_folder)

            !python TagNodeWithTopicJob.py \
                -r $runner_type \
                --strict-protocols \
                --no-bootstrap-mrjob \
                --no-output \
                --output-dir $mrjob_output_folder \
                --mapper-count $mapper_count \
                --reducer-count $reducer_count \
                $mrjob_graph_file \
                $mrjob_topic_file \
                2>> $debug_output

            return output_folder
```

6.1.3 Create MRJob to use character length as topic

Having a job which uses character length as topic allows us to do the Wikipedia example later (if we choose to do it) and also to use our PageRank test data as a sanity check.

```
In [ ]: from collections import defaultdict
        from mrjob.job import MRJob
        from mrjob.step import MRStep
        from mrjob.protocol import RawValueProtocol, ReprProtocol
```

```
import sys

class CharacterLengthAsTopicJob(MRJob):

    INPUT_PROTOCOL = RawValueProtocol
    INTERNAL_PROTOCOL = ReprProtocol
    OUTPUT_PROTOCOL = ReprProtocol

    def configure_options(self):
        super(CharacterLengthAsTopicJob, self).configure_options()

        self.add_passthrough_option('--mapper-count', type='int', default=1)

    """
    Accumulate the topic counts within a mapper.
    """
    def mapper(self, _, line):
        split_line = line.split('\t')

        name = split_line[0]
        node_id = split_line[1]

        yield node_id, str(len(name) % 10)

    """
    Set the mapper count options to make sure that MRJob creates enough mapper tasks.
    """
    def steps(self):
        step = MRStep(
            mapper = self.mapper,
            jobconf = {
                'mapreduce.job.maps': self.options.mapper_count
            })

        return [step]

if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
    job = CharacterLengthAsTopicJob()
    job.run()
```

Add a utility function to make it easy to call.

```
In [ ]: def character_length_as_topic_job(runner_type, indexes_file):
            output_folder = indexes_file + '.topics'

            remove_folder(runner_type, output_folder)

            mrjob_indexes_file = get_mrjob_path(runner_type, indexes_file)
            mrjob_output_folder = get_mrjob_path(runner_type, output_folder)

            !python CharacterLengthAsTopicJob.py \
                -r $runner_type \
                --strict-protocols \
                --no-bootstrap-mrjob \
                --no-output \
```

```
        --output-dir $mrjob_output_folder \
        --mapper-count $mapper_count \
        $mrjob_indexes_file \
        2>> $debug_output

    return output_folder
```

6.2 Create Topic-specific PageRank MRJob

6.2.1 Consider Irreducibility

Modify your PageRank implementation to produce a topic specific PageRank implementation, as described in:

http://www-cs-students.stanford.edu/~taherh/papers/topic-sensitive-pagerank.pdf

Note in this article that there is a special caveat to ensure that the transition matrix is irreducible. This caveat lies in footnote 3 on page 3:

> A minor caveat: to ensure that M is irreducible when p contains any 0 entries, nodes not reachable from nonzero nodes in p should be removed. In practice this is not problematic.

and must be adhered to for convergence to be guaranteed.

One final and important comment here: please consider the requirements for irreducibility with topic-specific PageRank. In particular, the literature ensures irreducibility by requiring that nodes not reachable from in-topic nodes be removed from the network.

This is not a small task, especially as it it must be performed separately for each of the (10) topics.

So, instead of using this method for irreducibility, please comment on why the literature's method is difficult to implement, and what what extra computation it will require.

Our first task is to remove the unreachable nodes from the outgoing links graph.

- Identify all unreachable nodes
- All unreachable nodes must be removed from the available nodes

First we would have to identify the unreachable nodes of the graph. To do this, we must perform a depth-first search of the graph. We start by performing an initial job which marks the topic nodes as the initial members of the queue and iterate. Rather than mark a node as visited, we can discard it from our graph after queueing the nodes on the frontier in order to reduce network overhead of re-transmitting the graph.

After identifying these nodes, we must remove them from our graph's list of available nodes. To do this, we must perform an anti-join of the original graph with our subgraph of unreachable nodes in order to derive a new graph containing only reachable nodes.

Our second task is to remove the unreachable nodes from the incoming links (the list of neighbors). To do this, we must essentially re-create our list of neighbors, but with the unreachable nodes filtered out.

- Derive the incoming links graph from the updated outgoing links graph
- All unreachable nodes must be removed from the incoming links graph
- Derive the outgoing links graph from the updated incoming links graph

First, we join the outgoing nodes graph with itself by following all edges in the outgoing links table and emitting the tuple `(neighbor, self)`. This results in an incoming links table.

After deriving this incoming links table, we must remove the unreachable nodes from the graph's list of available nodes. To do this, we must perform an anti-join of the derived incoming links graph with our subgraph of unreachable nodes in order to derive a new incoming links graph containing only reachable nodes.

Now that we've finally eliminated the unreachable nodes, we must join the updated incoming links graph with itself by following all edges in the incoming links table and emitting the tuple `(neighbor, self)` to then have the final outgoing nodes graph.

Each of these tasks is individually expensive, and all must be performed before we can even begin iterating over the graph in order to compute the topic-specific PageRank. As a result of all of this extra overhead, the literature's method may not be ideal as a homework assignment with time contraints on implementation.

6.2.2 Implement topic-specific PageRank algorithm

Then for your code, please use the alternative, non-uniform damping vector:

$v_{ji} = \beta(\frac{1}{|T_j|})$; if node i lies in topic T_j

$v_{ji} = (1-\beta)(\frac{1}{N-|T_j|})$; if node i lies outside of topic T_j

for $\beta \in (0,1)$ close to 1.

With this approach, you will not have to delete any nodes. If $\beta > 0.5$, PageRank is topic-sensitive, and if $\beta < 0.5$, the PageRank is anti-topic-sensitive. For any value of beta irreducibility should hold, so please try $\beta = 0.99$, and perhaps some other values locally, on the smaller networks.

As noted above, in order to avoid the downside of the computation described in the literature, we will instead avoid removal of the out of topic nodes and perform the following adjustment.

$$\text{weight}_{ij} = \begin{cases} \frac{\beta}{|T_j|} & \text{if } i \text{ in topic } T_j \\ \frac{1-\beta}{N-|T_j|} & \text{if } i \text{ not in topic } T_j \end{cases}$$

In this case, we set $\beta = 0.99$.

Topic-specific page rank is essentially identical to regular page rank, except that each phase it emits a page rank for each topic. PageRank is currently coded to make it easy to apply these specifying changes by overriding a few methods. These methods are detailed below.

```
In [ ]: from __future__ import division
        from mrjob.job import MRJob
        from mrjob.protocol import ReprProtocol
        from mrjob.step import MRStep
        from PageRankSingleIterationJob import PageRankSingleIterationJob
        import sys

        class TopicPageRankSingleIterationJob(PageRankSingleIterationJob):

            INPUT_PROTOCOL = ReprProtocol
            INTERNAL_PROTOCOL = ReprProtocol
            OUTPUT_PROTOCOL = ReprProtocol

            def configure_options(self):
                super(TopicPageRankSingleIterationJob, self).configure_options()
                self.add_passthrough_option('--beta', type='float', default=0.99)
```

```python
"""
Also initialize the total node count.
"""
def load_data(self):
    super(TopicPageRankSingleIterationJob, self).load_data()

    self.total_node_count = sum(self.node_count.values())
    self.node_count['NOBIAS'] = self.total_node_count

"""
Give all nodes uniform probability in the initial case.
"""
def parse_node_data(self, key, node_data):
    if len(node_data) < 3:
        initial_page_rank = 1.0 / self.total_node_count

        old_page_rank = {
            'NOBIAS': initial_page_rank
        }

        for topic in self.node_count.iterkeys():
            old_page_rank[topic] = initial_page_rank

        neighbors = node_data[0]
        metadata = node_data[1]
    else:
        old_page_rank = node_data[0]
        neighbors = node_data[2]
        metadata = node_data[3]

    return old_page_rank, neighbors, metadata

"""
Distribute mass evenly across all neighbors.
"""
def get_distributed_mass(self, key, old_page_rank, neighbor_count):
    distributed_mass = {
        topic: page_rank / neighbor_count
            for topic, page_rank in old_page_rank.iteritems()
    }

    return distributed_mass

"""
Return an empty dictionary.
"""
def get_empty_mass(self):
    return {}

"""
Sum the dictionaries together.
"""
def get_merged_mass(self, old_mass, new_mass):
    for key, value in new_mass.iteritems():
```

```
        if key in old_mass:
            old_mass[key] += value
        else:
            old_mass[key] = value

    return old_mass

"""
Damped mass is scaled for each value.
"""
def get_damped_mass(self, emit_mass):
    return {
        key: self.options.damping_factor * topic_mass
            for key, topic_mass in emit_mass.iteritems()
    }

"""
You only get the dangling bonus for your topic.
"""
def get_dangling_bonus(self, key, metadata):
    dangling_bonus = {}

    for topic, count in self.node_count.iteritems():
        dangling_mass = self.options.damping_factor * self.dangling_mass[topic]

        if count == self.total_node_count:
            multiplier = 1 / self.total_node_count
        elif topic == metadata:
            multiplier = self.options.beta / count
        else:
            multiplier = (1 - self.options.beta) / (self.total_node_count - count)

        dangling_bonus[topic] = dangling_mass * multiplier

    return dangling_bonus

"""
You only get the teleport bonus for your topic.
"""
def get_teleport_bonus(self, key, metadata):
    teleport_bonus = {}

    for topic, count in self.node_count.iteritems():
        teleport_mass = 1 - self.options.damping_factor

        if count == self.total_node_count:
            multiplier = 1 / self.total_node_count
        elif topic == metadata:
            multiplier = self.options.beta / count
        else:
            multiplier = (1 - self.options.beta) / (self.total_node_count - count)

        teleport_bonus[topic] = teleport_mass * multiplier
```

```
            return teleport_bonus

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = TopicPageRankSingleIterationJob()
        job.run()
```

6.2.3 Implement post-job computations

Next, we need to compute the probability mass associated with dangling nodes so that we can properly update our page rank computation, factoring in teleportation. Additionally, we want to check for convergence.

Most of this code is the same as the original PageRank convergence check, with the exception that we're working with multiple topic vectors rather than a single topic vector.

```
In [ ]: from __future__ import division
        from CheckPageRankConvergenceJob import CheckPageRankConvergenceJob
        from mrjob.protocol import ReprProtocol
        from mrjob.step import MRStep
        import sys

        class CheckTopicPageRankConvergenceJob(CheckPageRankConvergenceJob):

            INPUT_PROTOCOL = ReprProtocol
            INTERNAL_PROTOCOL = ReprProtocol
            OUTPUT_PROTOCOL = ReprProtocol

            """
            Also save the total node count across all topics.
            """
            def mapper_init(self):
                super(CheckTopicPageRankConvergenceJob, self).mapper_init()

                self.total_node_count = sum(self.node_count.values())
                self.node_count['NOBIAS'] = self.total_node_count

                self.dangling_mass = {}
                self.squared_rank_change = {}

                for topic in self.node_count.iterkeys():
                    self.dangling_mass[topic] = 0.0
                    self.squared_rank_change[topic] = 0.0

            """
            If we just initialized, there's no page rank to speak of. Otherwise, extract the
            metadata from the fields.
            """
            def parse_node_data(self, key, node_data):
                if len(node_data) < 3:
                    initial_page_rank = 1.0 / self.total_node_count

                    new_page_rank = {}

                    for topic in self.node_count.iterkeys():
                        new_page_rank[topic] = initial_page_rank

                    return new_page_rank, self.get_empty_mass(), node_data[0], node_data[1]
```

```python
        else:
            return node_data[0], node_data[1], node_data[2], node_data[3]

    """
    Return an empty dictionary.
    """
    def get_empty_mass(self):
        return {}

    """
    Return the mass as-is.
    """
    def get_dangling_mass(self, page_rank, metadata):
        if metadata not in page_rank:
            return None

        return {
            'NOBIAS': page_rank['NOBIAS'],
            metadata: page_rank[metadata]
        }

    """
    For each topic, compute the squared difference
    """
    def get_squared_rank_change(self, new_page_rank, old_page_rank):
        rank_change = {}

        for topic, new_value in new_page_rank.iteritems():
            if topic in old_page_rank:
                old_value = old_page_rank[topic]
                rank_change[topic] = (new_value - old_value) ** 2
            else:
                rank_change[topic] = new_value ** 2

        for topic, old_value in old_page_rank.iteritems():
            if topic not in new_page_rank:
                rank_change[topic] = old_value ** 2

        return rank_change

    """
    Sum the dictionaries together.
    """
    def get_merged_mass(self, old_mass, new_mass):
        for key, value in new_mass.iteritems():
            if key in old_mass:
                old_mass[key] += value
            else:
                old_mass[key] = value

        return old_mass

if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
    job = CheckTopicPageRankConvergenceJob()
```

```
        job.run()
```

6.3 Create Topic-specific PageRank driver

Next, provide a driver function which will run a specified number of iterations of the Topic-specific PageRank algorithm, starting from giving all nodes uniform weight, or until the PageRank algorithm converged. Note that since we're extending base classes, these need to be included during the MRJob setup phase.

```
In [ ]: !tar -zcf pagerank-source.tar.gz \
            PageRankSingleIterationJob.py \
            CheckPageRankConvergenceJob.py

        pagerank_source = '--setup \'export PYTHONPATH=$PYTHONPATH:pagerank-source.tar.gz#/\''
```

```
In [ ]: run_topic_page_rank = functools.partial(
            page_rank_driver,
            'TopicPageRankSingleIterationJob.py ' + pagerank_source,
            'CheckTopicPageRankConvergenceJob.py ' + pagerank_source)
```

6.4 Run Topic-specific PageRank on test data

As a sanity check, test the Topic-specific PageRank on the test data. We'll give each of the nodes the character length as a topic and then create use this updated file to perform a join with our existing graph.

```
In [ ]: !cat input/test/PageRank-test.txt.all/* | cut -d"'" -f 2 | awk '{print $1 "\t" $1 }' \
            > input/test/indices.txt

        test_topics = character_length_as_topic_job('inline', 'input/test/indices.txt')
        test_tagged_graph_file = tag_node_with_topic_job('inline', test_all, test_topics)
```

```
In [ ]: test_topic_counts = topic_occurrence_type_job('inline', test_topics)

        with open('node_count.txt', 'w') as node_count_file:
            json.dump(test_topic_counts, node_count_file)
```

```
In [ ]: %time test_topic_page_ranks = get_page_ranks( \
            'inline', run_topic_page_rank, test_tagged_graph_file, 'output/topic_test', \
            0.85, True)
```

```
2016-03-19 16:42:08.370560 PageRank converged after 50 iterations
CPU times: user 360 ms, sys: 928 ms, total: 1.29 s
Wall time: 39.3 s
```

Now we confirm that the values match up.

```
In [ ]: test_topic_names = [str(x) for x in test_topic_counts.keys()] + ['NOBIAS']

        pandas.DataFrame(sorted([
            (key, ) + tuple([node_data[0][str(topic_name)] for topic_name in test_topic_names])
                for key, node_data in test_topic_page_ranks.items()
        ]), columns = ['NodeId'] + test_topic_names)
```

Out[ ]:

	NodeId	1	NOBIAS
0	A	0.0328	0.0328
1	B	0.3844	0.3844
2	C	0.3429	0.3429

```
3        D  0.0391  0.0391
4        E  0.0809  0.0809
5        F  0.0391  0.0391
6        G  0.0162  0.0162
7        H  0.0162  0.0162
8        I  0.0162  0.0162
9        J  0.0162  0.0162
10       K  0.0162  0.0162
```

6.5 Acquire random network data

Run topic specific PageRank on the following randomly generated network of 100 nodes:

- s3://ucb-mids-mls-networks/randNet.txt (S3)
- https://www.dropbox.com/sh/2c0k5adwz36lkcw/AACEBW8MKuzl2L-tH_FmuG9ba/randNet.txt (Dropbox)

which are organized into ten topics, as described in the file:

- s3://ucb-mids-mls-networks/randNet_topics.txt (S3)
- https://www.dropbox.com/sh/2c0k5adwz36lkcw/AACTOoH1Oi03JxjOaW-Cy4N8a/randNet_topics.txt (Dropbox)

In [ ]:
```
randnet_out = get_dropbox_file(
    '2c0k5adwz36lkcw/AACEBW8MKuzl2L-tH_FmuG9ba', 'randNet', 'randNet.txt')
randnet_topics = get_dropbox_file(
    '2c0k5adwz36lkcw/AACTOoH1Oi03JxjOaW-Cy4N8a', 'randNet', 'randNet_topics.txt')
```

In [ ]:
```
split_for_hdfs(randnet_out)
split_for_hdfs(randnet_topics)
```

6.6 Run PageRank on random network data

In [ ]:
```
randnet_node_count = get_line_count('hadoop', randnet_out)

with open('node_count.txt', 'w') as node_count_file:
    json.dump(randnet_node_count, node_count_file)
```

In [ ]:
```
randnet_page_ranks = get_page_ranks( \
    'hadoop', run_page_rank, randnet_out, 'output/randNet', 0.85, True, False)
```

```
2016-03-19 16:59:58.917129 PageRank converged after 6 iterations
```

In [ ]:
```
pandas.DataFrame(sorted([
    (key, value[0]) for key, value in randnet_page_ranks.iteritems()
], key = lambda x: int(x[0])), columns = ['NodeId', 'NOBIAS'])
```

Out[ ]:

	NodeId	NOBIAS
0	1	0.0079
1	2	0.0103
2	3	0.0083
3	4	0.0090
4	5	0.0068
5	6	0.0097
6	7	0.0089
7	8	0.0101

8	9	0.0150
9	10	0.0111
10	11	0.0093
11	12	0.0097
12	13	0.0132
13	14	0.0099
14	15	0.0164
15	16	0.0077
16	17	0.0131
17	18	0.0064
18	19	0.0055
19	20	0.0051
20	21	0.0097
21	22	0.0052
22	23	0.0060
23	24	0.0074
24	25	0.0130
25	26	0.0079
26	27	0.0111
27	28	0.0115
28	29	0.0084
29	30	0.0089
30	31	0.0091
31	32	0.0133
32	33	0.0077
33	34	0.0090
34	35	0.0115
35	36	0.0060
36	37	0.0092
37	38	0.0074
38	39	0.0121
39	40	0.0084
40	41	0.0111
41	42	0.0094
42	43	0.0100
43	44	0.0089
44	45	0.0116
45	46	0.0105
46	47	0.0080
47	48	0.0080
48	49	0.0126
49	50	0.0069
50	51	0.0118
51	52	0.0143
52	53	0.0122
53	54	0.0092
54	55	0.0111
55	56	0.0114
56	57	0.0092
57	58	0.0148
58	59	0.0080
59	60	0.0057
60	61	0.0144
61	62	0.0106

```
62      63  0.0158
63      64  0.0071
64      65  0.0109
65      66  0.0087
66      67  0.0091
67      68  0.0092
68      69  0.0078
69      70  0.0131
70      71  0.0145
71      72  0.0082
72      73  0.0116
73      74  0.0160
74      75  0.0087
75      76  0.0058
76      77  0.0137
77      78  0.0103
78      79  0.0079
79      80  0.0091
80      81  0.0078
81      82  0.0046
82      83  0.0102
83      84  0.0106
84      85  0.0152
85      86  0.0107
86      87  0.0086
87      88  0.0131
88      89  0.0072
89      90  0.0129
90      91  0.0110
91      92  0.0136
92      93  0.0067
93      94  0.0111
94      95  0.0111
95      96  0.0060
96      97  0.0102
97      98  0.0095
98      99  0.0115
99     100  0.0154
```

6.7 Run Topic-specific PageRank on random network data

> Since there are 10 topics, your result should be 11 PageRank vectors (one for the vanilla PageRank implementation in 9.1, and one for each topic with the topic specific implementation).

We can go ahead and run the topic-specific page rank on this data set after tagging the graph.

```
In [ ]: randnet_tagged_graph_file = tag_node_with_topic_job(
            'hadoop', randnet_out, randnet_topics)
```

```
In [ ]: randnet_topic_counts = topic_occurrence_type_job('hadoop', randnet_topics)

        with open('node_count.txt', 'w') as node_count_file:
            json.dump(randnet_topic_counts, node_count_file)
```

```
In [ ]: %time randnet_topic_page_ranks = get_page_ranks( \
```

```
            'hadoop', run_topic_page_rank, randnet_tagged_graph_file, 'output/topic_randNet', \
            0.85, True, False)
```

```
2016-03-19 17:28:47.621090 PageRank converged after 7 iterations
CPU times: user 15.8 s, sys: 2.44 s, total: 18.2 s
Wall time: 18min 39s
```

Now we can confirm that we actually have 11 PageRank vectors.

```
In [ ]: randnet_topic_names = ['NOBIAS'] + [str(x) for x in randnet_topic_counts.keys()]

        randnet_data = []

        for key, node_data in randnet_topic_page_ranks.items():
            value = [node_data[0][str(topic_name)] for topic_name in randnet_topic_names]
            row = (key, node_data[2]) + tuple(value)
            randnet_data.append(row)

        randnet_data_frame = pandas.DataFrame(
            sorted(randnet_data, key = lambda x: int(x[0])),
            columns = ['NodeId', 'Topic'] + randnet_topic_names)
```

6.8 Check topic PageRank after convergence

Print out the top ten ranking nodes and their topics for each of the 11 versions, and comment on your result. Assume a teleportation factor of 0.15 in all your analyses.

6.8.1 Check top 10 composition

First, extract the top 10 for each topic and present each one as a data frame so we can see if the majority of the top 10 are documents that are actually about the topic (so just how heavily the high popularity pages influence the rankings).

```
In [ ]: for topic_name in randnet_topic_names:
            by_pagerank = randnet_data_frame.sort_values(topic_name, ascending = False)
            display(by_pagerank[:10][['NodeId', 'Topic', topic_name]])
```

	NodeId	Topic	NOBIAS
14	15	3	0.0164
73	74	10	0.0160
62	63	4	0.0158
99	100	8	0.0154
84	85	7	0.0152
8	9	2	0.0150
57	58	2	0.0148
70	71	2	0.0145
60	61	8	0.0144
51	52	1	0.0143

	NodeId	Topic	1
31	32	1	0.0206
76	77	1	0.0205
51	52	1	0.0198
91	92	1	0.0195
9	10	1	0.0186

26	27	1	0.0185
84	85	7	0.0178
97	98	1	0.0177
45	46	1	0.0175
73	74	10	0.0160

	NodeId	Topic	2
57	58	2	0.0308
70	71	2	0.0297
8	9	2	0.0293
72	73	2	0.0289
11	12	2	0.0269
58	59	2	0.0258
74	75	2	0.0248
81	82	2	0.0229
51	52	1	0.0163
16	17	10	0.0152

	NodeId	Topic	3
14	15	3	0.0315
69	70	3	0.0271
85	86	3	0.0265
90	91	3	0.0245
65	66	3	0.0241
1	2	3	0.0237
30	31	3	0.0228
39	40	3	0.0222
19	20	3	0.0197
73	74	10	0.0159

	NodeId	Topic	4
62	63	4	0.0262
82	83	4	0.0218
64	65	4	0.0206
77	78	4	0.0202
40	41	4	0.0199
83	84	4	0.0195
78	79	4	0.0184
37	38	4	0.0175
14	15	3	0.0168
71	72	4	0.0167

	NodeId	Topic	5
98	99	5	0.0290
89	90	5	0.0283
87	88	5	0.0272
50	51	5	0.0268
44	45	5	0.0256
4	5	5	0.0239
33	34	5	0.0239
3	4	5	0.0234

79	80	5	0.0228
99	100	8	0.0167

	NodeId	Topic	6
12	13	6	0.0346
55	56	6	0.0329
36	37	6	0.0318
10	11	6	0.0313
68	69	6	0.0301
22	23	6	0.0283
14	15	3	0.0172
84	85	7	0.0170
51	52	1	0.0166
73	74	10	0.0155

	NodeId	Topic	7
84	85	7	0.0268
24	25	7	0.0266
27	28	7	0.0248
52	53	7	0.0248
34	35	7	0.0242
96	97	7	0.0234
46	47	7	0.0229
54	55	7	0.0226
29	30	7	0.0221
49	50	7	0.0201

	NodeId	Topic	8
99	100	8	0.0329
60	61	8	0.0279
38	39	8	0.0272
7	8	8	0.0272
61	62	8	0.0253
86	87	8	0.0253
5	6	8	0.0235
53	54	8	0.0229
17	18	8	0.0206
8	9	2	0.0154

	NodeId	Topic	9
93	94	9	0.0302
13	14	9	0.0295
41	42	9	0.0292
20	21	9	0.0284
56	57	9	0.0275
95	96	9	0.0263
23	24	9	0.0258
62	63	4	0.0172
60	61	8	0.0164
73	74	10	0.0143

```
   NodeId Topic      10
73     74    10  0.0263
16     17    10  0.0236
48     49    10  0.0236
94     95    10  0.0206
6       7    10  0.0199
42     43    10  0.0194
67     68    10  0.0190
47     48    10  0.0190
0       1    10  0.0190
2       3    10  0.0186
```

In each of the topic-specific rankings, the top 10 nodes are largely part of the topic of interest. In all cases, the top 6 ranked nodes are all part of the topic of interest. A few exceptions are within topic 1, where the 7th ranked node is from topic 7, and in topic 6, where the 7th ranked node is topic 3.

6.8.2 Check top 10 repetitions

Next, see if there are any obvious trends when viewing the raw ranks together as a grid.

In [ ]:
```
randnet_top10 = OrderedDict()

for topic_name in randnet_topic_names:
    by_pagerank = randnet_data_frame.sort_values(topic_name, ascending = False)
    top10_pages = by_pagerank[:10]['NodeId'].tolist()
    randnet_top10[topic_name] = top10_pages

pandas.DataFrame(randnet_top10)
```

Out[ ]:

	NOBIAS	1	2	3	4	5	6	7	8	9	10
0	15	32	58	15	63	99	13	85	100	94	74
1	74	77	71	70	83	90	56	25	61	14	17
2	63	52	9	86	65	88	37	28	39	42	49
3	100	92	73	91	78	51	11	53	8	21	95
4	85	10	12	66	41	45	69	35	62	57	7
5	9	27	59	2	84	5	23	97	87	96	43
6	58	85	75	31	79	34	15	47	6	24	68
7	71	98	82	40	38	4	85	55	54	63	48
8	61	46	52	20	15	80	52	30	18	61	1
9	52	74	17	74	72	100	74	50	9	74	3

There appear to be some pages that appear multiple times (such as 15 and 74, which have the highest values in the NOBIAS column), so it would be good to see if which pages appear often that are not obvious at a glance.

In [ ]:
```
randnet_popularity = defaultdict(int)

for page in numpy.array(randnet_top10.values()).flatten():
    randnet_popularity[page] += 1

randnet_popularity_df = pandas.DataFrame([
    (page, count) for page, count in randnet_popularity.iteritems()
], columns = ['NodeId', 'Count'])

randnet_multi_top10 = randnet_popularity_df[randnet_popularity_df['Count'] != 1]
randnet_multi_top10.sort_values('Count', ascending = False)
```

Out[ ]:

	NodeId	Count
52	74	6
18	85	4
69	15	4
80	52	4
4	61	3
6	63	3
41	9	3
59	100	3
55	71	2
70	58	2
71	17	2

We can see that from this top 10 list, pages 63, 100, 15, 9, and 74 appear more than 5 times across all topics and are in the top 6 in the unbiased PageRank. This suggests that either the algorithm is unable to fully remove the influence of these top 5 pages, or that these pages are authoritative on many topics.

7 HW 9.5: Applying topic-specific PageRank to Wikipedia

7.1 Create a job to sort by topic-specific PageRank

In [ ]:

```
from collections import defaultdict
import heapq
import math
from mrjob.job import MRJob
from mrjob.step import MRStep
from mrjob.protocol import ReprProtocol
import sys

class TopicPageRankTopNJob(MRJob):

    INPUT_PROTOCOL = ReprProtocol
    INTERNAL_PROTOCOL = ReprProtocol
    OUTPUT_PROTOCOL = ReprProtocol

    """
    Allow configuration of the N used for the top-N job.
    """
    def configure_options(self):
        super(TopicPageRankTopNJob, self).configure_options()
        self.add_passthrough_option('--n', default=10, type='int')
        self.add_passthrough_option('--mapper-count', default=1, type='int')
        self.add_passthrough_option('--reducer-count', default=1, type='int')

    """
    Initialize our priority queue to an empty list.
    """
    def mapper_init(self):
        self.top_n = defaultdict(list)

    """
    Buffer the top N results on the mapper side so that we can emit them during the final
    stage to reduce the amount of network traffic. Allows single reducer approach to work
    for larger networks like the Wikipedia graph.
```

```
"""
def mapper(self, key, node_data):
    old_page_rank = node_data[0]

    # Use log page rank in case we decide to switch over to Hadoop sort rather
    # than an in-memory sort for the reducer.

    for topic, page_rank in old_page_rank.iteritems():
        topic_top_n = self.top_n[topic]

        log_page_rank = math.log(page_rank)
        heap_value = (log_page_rank, key) + node_data

        if len(topic_top_n) == self.options.n:
            heapq.heappushpop(topic_top_n, heap_value)
        else:
            heapq.heappush(topic_top_n, heap_value)

"""
Emit each of the items to the None key so that we can perform a reducer-side sort.
"""
def mapper_final(self):
    for topic, topic_top_n in self.top_n.iteritems():
        for item in topic_top_n:
            yield topic, item

"""
Reducer which accumulates the top N and then emits them.
"""
def reducer(self, topic, all_items):
    top_n = []

    for item in all_items:
        if len(top_n) == self.options.n:
            heapq.heappushpop(top_n, item)
        else:
            heapq.heappush(top_n, item)

    for item in heapq.nlargest(self.options.n, top_n):
        yield topic, item[1:]

"""
Set the mapper and reducer count options to make sure that MRJob creates enough
mapper/reducer tasks.
"""
def steps(self):
    step = MRStep(
        mapper_init = self.mapper_init, mapper = self.mapper,
        mapper_final = self.mapper_final, reducer = self.reducer,
        jobconf = {
            'mapreduce.job.maps': self.options.mapper_count,
            'mapreduce.job.reduces': self.options.reducer_count
        })
```

```
            return [step]

    if __name__ == '__main__' and sys.argv[0].find('ipykernel') == -1:
        job = TopicPageRankTopNJob()
        job.run()
```

Add a utility method to make it easy to call.

```
In [ ]: def topic_page_rank_top_n_job(runner_type, graph_file, n, reducer_count):
            output_folder = graph_file + '.top' + str(n)

            if not folder_exists(runner_type, output_folder):
                mrjob_graph_file = get_mrjob_path(runner_type, graph_file)
                mrjob_output_folder = get_mrjob_path(runner_type, output_folder)

                !python TopicPageRankTopNJob.py \
                    -r $runner_type \
                    --strict-protocols \
                    --no-bootstrap-mrjob \
                    --no-output \
                    --n $n \
                    --mapper-count $mapper_count \
                    --reducer-count $reducer_count \
                    --output-dir $mrjob_output_folder \
                    $mrjob_graph_file \
                    2>> $debug_output

            output = pipe_cat_output(runner_type, output_folder)

            topn_graph = defaultdict(list)

            for line in output.split('\n'):
                topic, result = line.split('\t', 1)

                topic = eval(topic)
                value = eval(result)

                topn_graph[topic].append(value)

            return topn_graph
```

7.2 Prepare Wikipedia for topic-specific PageRank

Here you will apply your topic-specific PageRank implementation to Wikipedia, defining topics (very arbitrarily) for each page by the length (number of characters) of the name of the article mod 10, so that there are 10 topics.

We'll give each of the nodes the character length as a topic and then create use this updated file to perform a join with our existing graph.

```
In [ ]: %time wikipedia_topics = character_length_as_topic_job('hadoop', wikipedia_indices)

Deleted /user/ubuntu/input/wikipedia/indices.txt.topics
CPU times: user 1.24 s, sys: 167 ms, total: 1.41 s
Wall time: 1min 26s
```

```
In [ ]: %time wikipedia_tagged_graph_file = tag_node_with_topic_job( \
            'hadoop', wikipedia_all, wikipedia_topics)
```

```
Deleted /user/ubuntu/input/wikipedia/all-pages-indexed-out.txt.all.topic_tagged
CPU times: user 6.09 s, sys: 867 ms, total: 6.95 s
Wall time: 7min 33s
```

```
In [ ]: %time wikipedia_topic_counts = topic_occurrence_type_job('hadoop', wikipedia_topics)

        with open('node_count.txt', 'w') as node_count_file:
            json.dump(wikipedia_topic_counts, node_count_file)
```

```
CPU times: user 0 ns, sys: 26.8 ms, total: 26.8 ms
Wall time: 9.81 s
```

```
In [ ]: run_wikipedia_topic_page_ranks = functools.partial(
            run_topic_page_rank, 'hadoop', wikipedia_tagged_graph_file, 'output/topic_wikipedia',
            0.85)
```

7.3 Check topic-specific PageRank after 5 iterations

Once again, print out the top ten ranking nodes and their topics for each of the 11 versions, and comment on your result. Assume a teleportation factor of 0.15 in all your analyses.

```
In [ ]: %time unsorted_wikipedia_topic_page_ranks_05 = \
            run_wikipedia_topic_page_ranks(5, 0, True, False, True)
```

```
2016-03-19 18:24:13.860565 Running convergence check for iteration 0
Deleted /user/ubuntu/output/wikipedia/all-pages-indexed-out.txt.all.topic_tagged.converge_summary
2016-03-19 18:26:53.048604 Running PageRank iteration 1
2016-03-19 19:22:43.425347 Running convergence check for iteration 1
2016-03-19 19:26:29.560826 Running PageRank iteration 2
2016-03-19 20:06:20.101728 Running convergence check for iteration 2
2016-03-19 20:09:56.836308 Running PageRank iteration 3
2016-03-19 20:51:34.768556 Running convergence check for iteration 3
2016-03-19 20:55:15.234877 Running PageRank iteration 4
2016-03-19 21:37:02.687830 Running convergence check for iteration 4
2016-03-19 21:40:48.706463 Running PageRank iteration 5
2016-03-19 22:20:08.027225 Running convergence check for iteration 5
CPU times: user 3min 8s, sys: 21.9 s, total: 3min 30s
Wall time: 3h 59min 43s
```

7.4 Check top ranking nodes for each topic

```
In [ ]: %time top100_wikipedia_topic_page_ranks_05 = topic_page_rank_top_n_job( \
            'hadoop', unsorted_wikipedia_topic_page_ranks_05, 10, \
            len(wikipedia_topic_counts))
```

```
CPU times: user 242 ms, sys: 28.4 ms, total: 271 ms
Wall time: 10.4 s
```

First, we look at it individually.

```
In [ ]: for topic, top10 in sorted(top100_wikipedia_topic_page_ranks_05.iteritems()):
            top10_data = [
                (item[0], item[4], item[1][topic]) for item in top10
```

```
    ]

    top10_df = pandas.DataFrame(top10_data, columns = ['NodeId', 'Topic', topic])
    display(top10_df)
```

```
     NodeId Topic       0
0  13455888     3  0.0008
1   1184351     6  0.0005
2   4695850     6  0.0004
3   5051368     7  0.0003
4   1384888     9  0.0003
5   6113490     6  0.0003
6   7902219     4  0.0003
7   6076759     5  0.0002
8   2437837     6  0.0002
9  13425865     4  0.0002


     NodeId Topic       1
0  13455888     3  0.0008
1   1184351     6  0.0004
2   4695850     6  0.0003
3   5051368     7  0.0003
4   1384888     9  0.0003
5   6113490     6  0.0003
6   2437837     6  0.0003
7   4196067     7  0.0002
8  13425865     4  0.0002
9   6076759     5  0.0002


     NodeId Topic       2
0  13455888     3  0.0008
1   1184351     6  0.0004
2   4695850     6  0.0003
3   5051368     7  0.0003
4   2437837     6  0.0003
5  13425865     4  0.0003
6   4196067     7  0.0002
7   1384888     9  0.0002
8   6113490     6  0.0002
9   6076759     5  0.0002


     NodeId Topic       3
0  10527224     7  0.0010
1   5490435     6  0.0009
2  13455888     3  0.0008
3   4695850     6  0.0003
4   1184351     6  0.0003
5   5051368     7  0.0003
6   2437837     6  0.0003
7   4196067     7  0.0003
8  13425865     4  0.0002
9   6076759     5  0.0002
```

	NodeId	Topic	4
0	13455888	3	0.0008
1	4695850	6	0.0003
2	5051368	7	0.0003
3	1184351	6	0.0003
4	2437837	6	0.0003
5	4196067	7	0.0002
6	13425865	4	0.0002
7	6416278	5	0.0002
8	6076759	5	0.0002
9	14112583	2	0.0002

	NodeId	Topic	5
0	13455888	3	0.0008
1	4695850	6	0.0004
2	5051368	7	0.0003
3	1184351	6	0.0003
4	2437837	6	0.0002
5	7902219	4	0.0002
6	4196067	7	0.0002
7	13425865	4	0.0002
8	6076759	5	0.0002
9	6172466	4	0.0002

	NodeId	Topic	6
0	13455888	3	0.0008
1	4695850	6	0.0004
2	1184351	6	0.0003
3	5051368	7	0.0003
4	7902219	4	0.0003
5	6172466	4	0.0003
6	6076759	5	0.0002
7	2437837	6	0.0002
8	13425865	4	0.0002
9	15164193	7	0.0002

	NodeId	Topic	7
0	13455888	3	0.0008
1	4695850	6	0.0004
2	1184351	6	0.0004
3	5051368	7	0.0003
4	7902219	4	0.0003
5	6172466	4	0.0003
6	15164193	7	0.0003
7	1384888	9	0.0003
8	6113490	6	0.0003
9	6076759	5	0.0002

	NodeId	Topic	8
0	13455888	3	0.0008
1	1184351	6	0.0004

2	4695850	6	0.0004
3	5051368	7	0.0003
4	1384888	9	0.0003
5	6113490	6	0.0003
6	7902219	4	0.0003
7	15164193	7	0.0003
8	6172466	4	0.0003
9	6076759	5	0.0003

	NodeId	Topic	9
0	13455888	3	0.0008
1	1184351	6	0.0005
2	4695850	6	0.0004
3	5051368	7	0.0004
4	1384888	9	0.0003
5	6113490	6	0.0003
6	7902219	4	0.0003
7	6076759	5	0.0003
8	6172466	4	0.0002
9	15164193	7	0.0002

	NodeId	Topic	NOBIAS
0	13455888	3	0.0015
1	1184351	6	0.0007
2	4695850	6	0.0006
3	5051368	7	0.0006
4	1384888	9	0.0005
5	7902219	4	0.0005
6	6113490	6	0.0005
7	2437837	6	0.0004
8	6076759	5	0.0004
9	13425865	4	0.0004

Essentially, we've discovered that it's not likely that pages with similar length names will link to each other, since there's no real pattern within the topics. There appear to be a lot of commonalities. We can look at the table as a grid and see how much overlap there is.

In [ ]:
```
wikipedia_top10 = {}

for topic, top10 in sorted(top100_wikipedia_topic_page_ranks_05.iteritems()):
    wikipedia_top10[topic] = [item[0] for item in top10]

pandas.DataFrame(wikipedia_top10)
```

Out[ ]:

	0	1	2	3	4	5	6 \
0	13455888	13455888	13455888	10527224	13455888	13455888	13455888
1	1184351	1184351	1184351	5490435	4695850	4695850	4695850
2	4695850	4695850	4695850	13455888	5051368	5051368	1184351
3	5051368	5051368	5051368	4695850	1184351	1184351	5051368
4	1384888	1384888	2437837	1184351	2437837	2437837	7902219
5	6113490	6113490	13425865	5051368	4196067	7902219	6172466
6	7902219	2437837	4196067	2437837	13425865	4196067	6076759

7	6076759	4196067	1384888	4196067	6416278	13425865	2437837
8	2437837	13425865	6113490	13425865	6076759	6076759	13425865
9	13425865	6076759	6076759	6076759	14112583	6172466	15164193

	7	8	9	NOBIAS
0	13455888	13455888	13455888	13455888
1	4695850	1184351	1184351	1184351
2	1184351	4695850	4695850	4695850
3	5051368	5051368	5051368	5051368
4	7902219	1384888	1384888	1384888
5	6172466	6113490	6113490	7902219
6	15164193	7902219	7902219	6113490
7	1384888	15164193	6076759	2437837
8	6113490	6172466	6172466	6076759
9	6076759	6076759	15164193	13425865

It appears as though there is quite a bit of overlap. Therefore, what we essentially see is that the algorithm is not fundamentally from uniform mass re-distribution as a result of the poor choice in topics, and ultimately the highest ranked items in the `NOBIAS` category wind up dominating all the other topics as well.