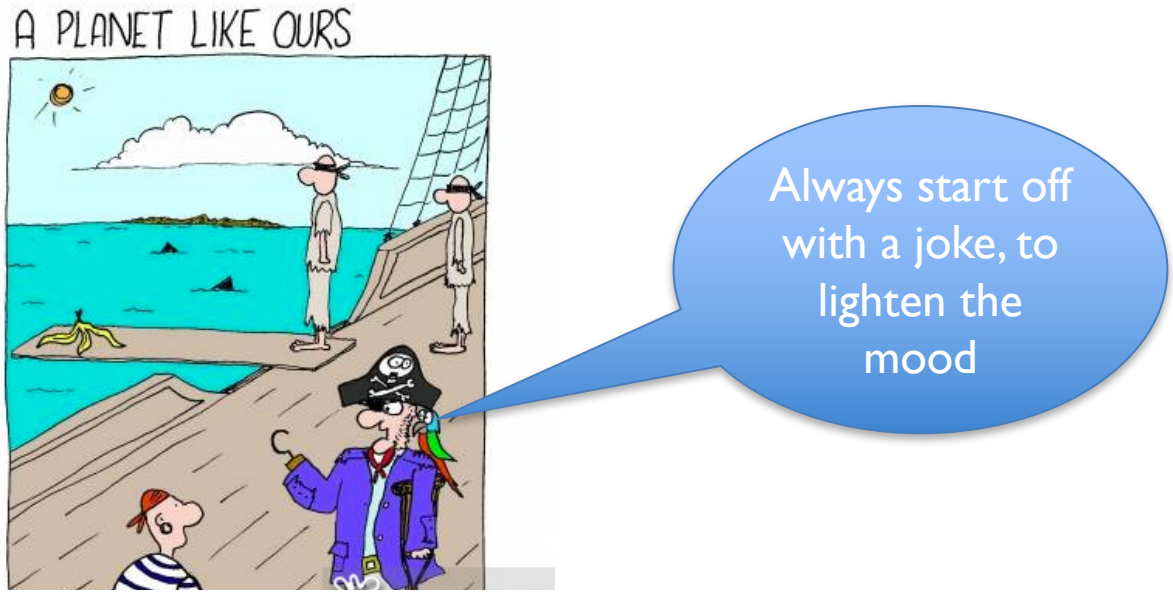


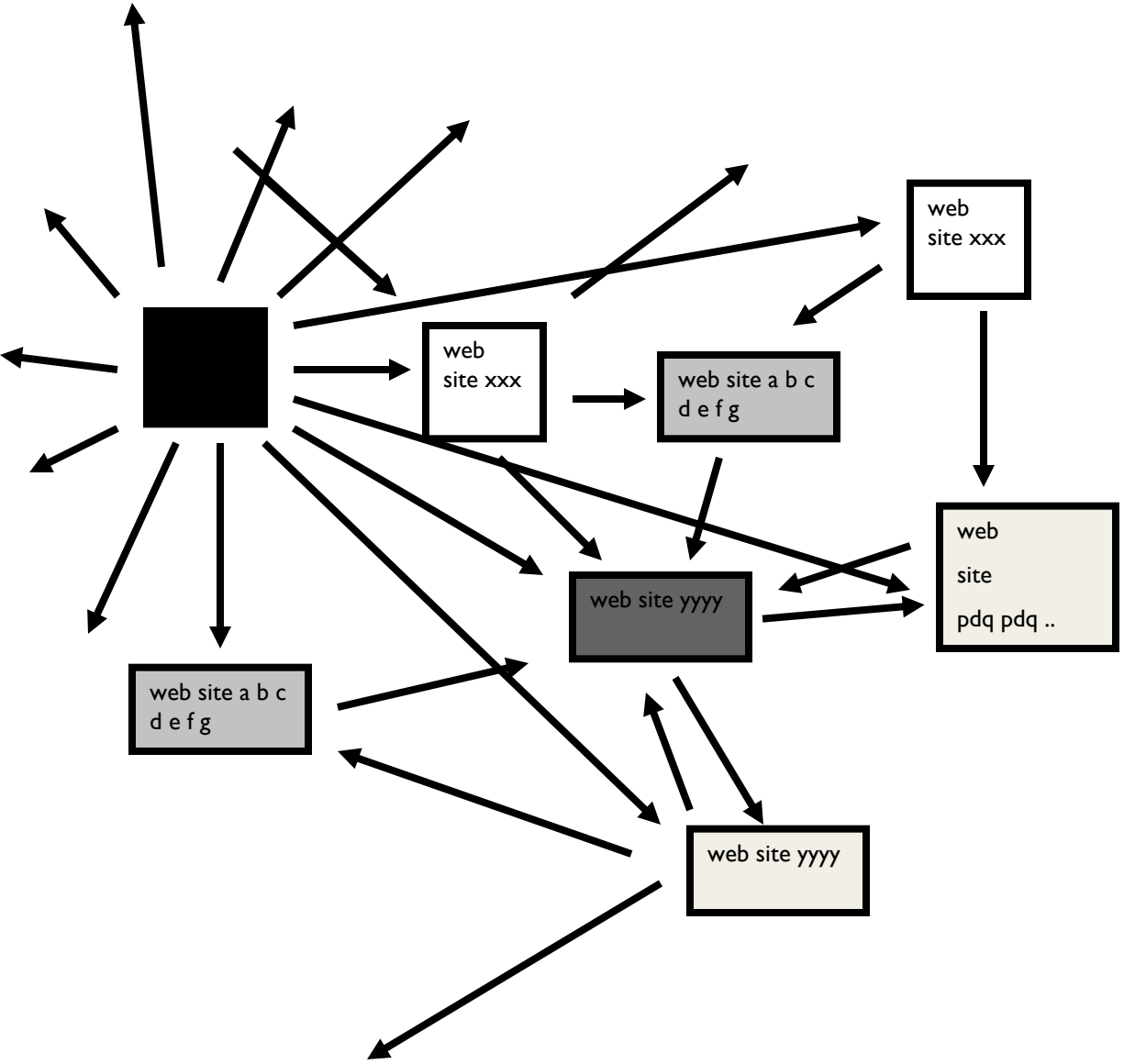
Workflows 3: Graphs, PageRank, Loops, Spark

The course so far

- Cost of operations
- Streaming learning algorithms
  - Parallel streaming with map-reduce
  - Building complex parallel algorithms with dataflow languages (Pig, GuineaPig, ….)
    - Mostly for **text**
- Another common large data structure: **graphs**
    - Examples: web, Facebook, Twitter, citation data, Freebase, Wikipedia, biological networks, …
  - PageRank in dataflow languages
  - Iteration in dataflow
  - Spark
- Catchup: similarity joins

PageRank

Google's PageRank



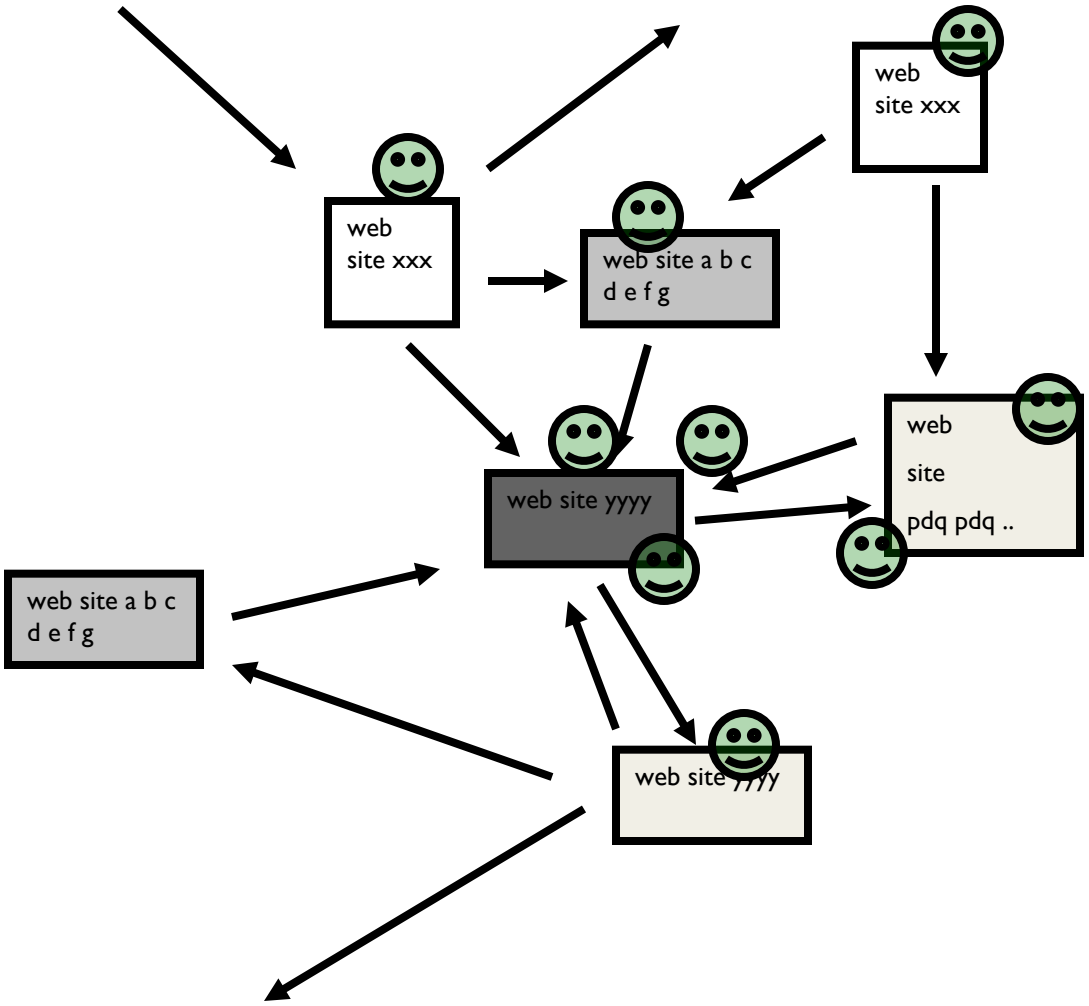
Inlinks are "good" (recommendations)

Inlinks from a "good" site are better than inlinks from a "bad" site

but inlinks from sites with many outlinks are not a "good"...

"Good " and "bad" are relative.

Google's PageRank

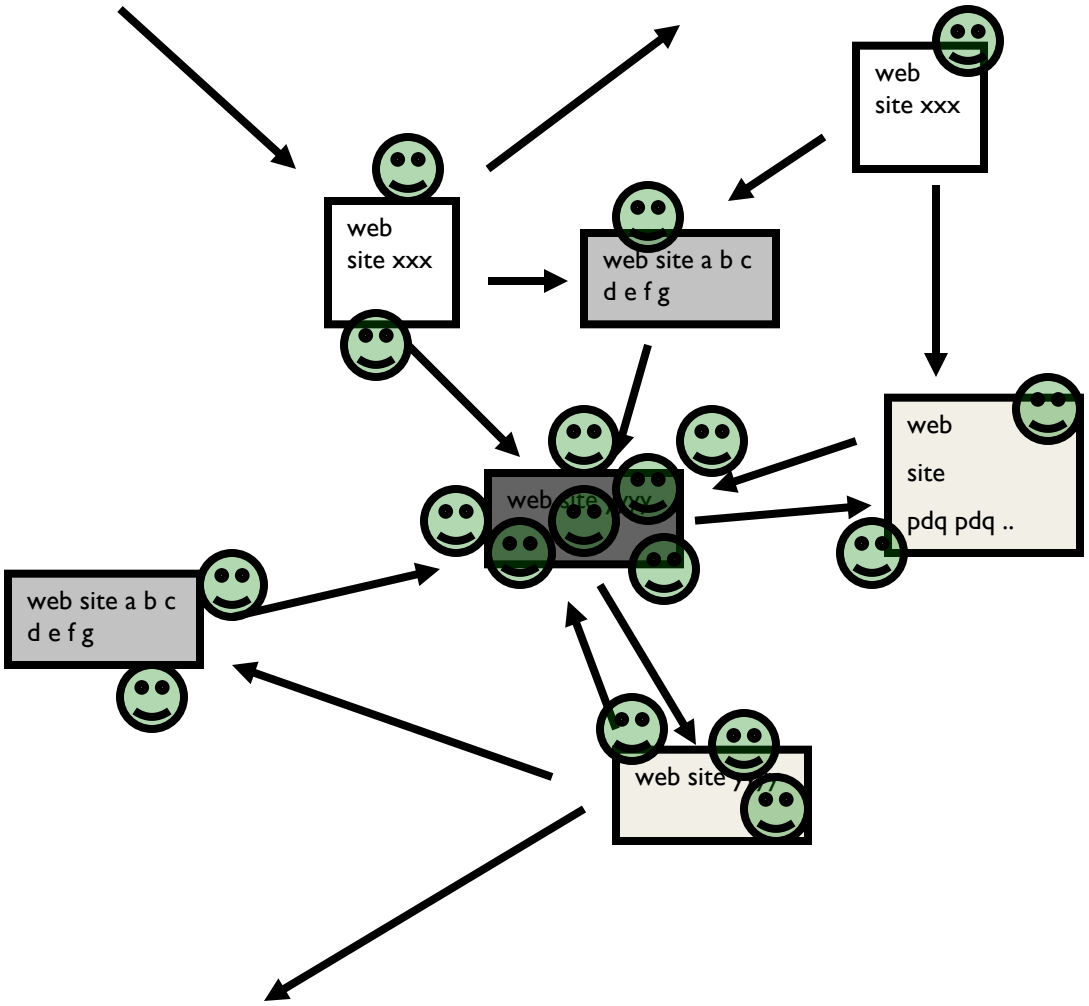


Imagine a "pagehopper" that always either

- follows a random link, or
- jumps to random page

Google's PageRank

(Brin & Page, http://www-db.stanford.edu/~backrub/google.html)



Imagine a "pagehopper" that always either

- follows a random link, or
- jumps to random page

PageRank ranks pages by the amount of time the pagehopper spends on a page:

- or, if there were many pagehoppers, PageRank is the expected "crowd size"

PageRank in Memory

- Let $\mathbf{u} = (1/N, \ldots, 1/N)$
  - dimension = #nodes N
- Let A = adjacency matrix: $[a_{ij}=1 \Leftrightarrow$ i links to j$]$
- Let $W = [w_{ij} = a_{ij}/\text{outdegree}(i)]$
  - w_{ij} is probability of jump from i to j
- Let $\mathbf{v}^0 = (1,1,\ldots,1)$
  - or anything else you want
- Repeat until converged:
  - Let $\mathbf{v}^{t+1} = c\mathbf{u} + (1\text{-}c)\ \mathbf{v}^t\mathbf{W}$
    - c is probability of jumping "anywhere randomly"

Streaming PageRank

Streaming PageRank

- Assume we can store **v** but not **W** in memory
- Repeat until converged:
  - Let $\mathbf{v}^{t+1} = c\mathbf{u} + (1\text{-}c)\,\mathbf{v}^t\mathbf{W}$

each iteration: from v, compute v', then let v=v'

- **W** is a *sparse row matrix*: each line is
  - i $j_{i,1},\ldots,j_{i,d}$ [the neighbors of i]
- Store **v'** and **v** in memory: **v'** starts out as c**u**
- For each line "i $j_{i,1},\ldots,j_{i,d}$ "
  - For each j in $j_{i,1},\ldots,j_{i,d}$
    - **v'**[j] += (1-c)**v[i]**/d

Everything needed for update is right there in row….

Streaming PageRank

- Assume we can store **one row** of W in memory at a time, but <u>not **v**</u> – i.e., links on a web page fit in memory, not pageRank values for the whole web.
- Repeat until converged:
  - Let $\mathbf{v}^{t+1} = c\mathbf{u} + (1\text{-}c)\ \mathbf{v}^t\mathbf{W}$

Like in naïve Bayes: a document fits, but the model doesn't

- Store **W** as a row matrix: each line is
  - i $j_{i,1},\ldots,j_{i,d}$ [the neighbors of i]
- **v'** starts out as c**u**
- For each line "i $j_{i,1},\ldots,j_{i,d}$ "
  - For each j in $j_{i,1},\ldots,j_{i,d}$
    - **v'**[j] += (1-c)v[i]/d

We need to convert these counter updates to messages, like we did for naïve Bayes

Streaming PageRank

- Assume we can store **one row** of W in memory at a time, but not **v** – i.e., links on a web page fit in memory, not pageRank for the whole web.
- Repeat until converged:
  - Let $\mathbf{v}^{t+1} = c\mathbf{u} + (1\text{-}c)\ \mathbf{v}^t\mathbf{W}$

- Store **W** as a row matrix: each line is
  - i $j_{i,1},\ldots,j_{i,d}$ [the neighbors of i]
- **v'** starts out as c**u**
- For each line "i $j_{i,1},\ldots,j_{i,d}$ "
  - For each j in $j_{i,1},\ldots,j_{i,d}$
    - **v'**[j] += (1-c)v[i]/d

Streaming: if we know c, v[i] and have the linked-to j's then

- we can compute d
- we can produce messages saying how much to increment each v[j]

Then we sort the messages by v[j] and add up all the increments

- and somehow also add in c/N

eRank

- **one row** of W in memory at a time,
  a web page fit in memory, not
  le web.

So we need to stream thru some structure that has v[i] plus all the outlinks from i

This is a copy of the graph with current pageRank estimates (**v**) for each node attached to the node.

- Store **W** as a row matrix: each line is
  - i $j_{i,1},\ldots,j_{i,d}$ [the neighbors of i]
- **v'** starts out as c**u**
- For each line "i $j_{i,1},\ldots,j_{i,d}$ "
  - For each j in $j_{i,1},\ldots,j_{i,d}$
    - **v'**[j] += (1-c)v[i]/d

Streaming: if we know c, v[i] and have the linked-to j's then

- we can compute d
- we can produce messages saying how much to increment each v[j]

Then we sort the messages by v[j] and add up all the increments

- and somehow also add in c/N

PageRank in Dataflow Languages

Iteration in Dataflow

- PIG and Guinea Pig are *pure* data flow languages
  - no conditionals
  - no iteration
- To loop you need to embed a dataflow program into a 'real' program

```
#!/usr/bin/python
from org.apache.pig.scripting import *

P = Pig.compile("""
pig script: PR(A) = (1-d) + d (PR(T1)/C(T1) + ... + PR(Tn)/C(Tn))
""")

params = { 'd': '0.5', 'docs_in': 'data/pagerank_data_simple' }

for i in range(10):
    out = "out/pagerank_data_" + str(i + 1)
    params["docs_out"] = out
    Pig.fs("rmr " + out)
    stats = P.bind(params).runSingle()
    if not stats.isSuccessful():
        raise 'failed'
    params["docs_in"] = out
```

params: d, docs_in, docs_out

Iterate 10 times

Pass parameters as a dictionary

Just run P, that was declared above

The output becomes the new input

Recap: a Gpig program….

```
# always start like this
from guineapig import *
import sys

# supporting routines can go here
def tokens(line):
    for tok in line.split():
        yield tok.lower()

#always subclass Planner
class WordCount(Planner):

    wc = ReadLines('corpus.txt') | Flatten(by=tokens) | Group(by=lambda x:x, r

# always end like this
if __name__ == "__main__":
    WordCount().main(sys.argv)
```

There's no "program" object, and no obvious way to write a main that will call a program

grammatically

Creatiing a Planner object I can call (not a subclass) – remember to call setup()

```
def pageRankPlanner():

    p = Planner()

    p.x = ReadLines(...) | ...
    p.y = Map(p.x, by=....)
    ...
    p.setup()
    return p

if __name__ == "__main__":
    #run subplan step, if called recu
    if Planner.partOfPlan(sys.argv):
        pageRankPlanner().main(sys.ar
    else:
        # run your actual main here
        # for instance:
        planner = pageRankPlanner()
        v = planner.getView('wordcount')
        v.storagePlan().execute(planner)
```

Somewhere in the execution of the plan we will call *this script* with special arguments that tell it to do a substep of the plan.

So we need a Python *main* that will do that right

But I also want to write an actual main program so….

Calling GuineaPig pro tically

```
if __name__ == "__main__":

    #run subplan step, if called recursively
    if Planner.partOfPlan(sys.argv):
        pageRankPlanner().main(sys.argv)

    else:

        #create the initial graph w pagerank
        planner = pageRankPlanner()
        v0 = planner.getView('serializedInitRankedGraph')
        v0.storagePlan().execute(planner)
        print '>>> moving initial pageranks to',TMP
        os.rename(v0.storedFile(), TMPFILE)

        for i in range(N):
            print '>>> pagerank iteration',i
            vi = planner.getView('serializedRankedGra
            vi.storagePlan().execute(planner)
            print '>>> moving round',i,'pageranks to',TMPFILE
            os.rename(vi.storedFile(), TMPFILE)
```

create the planner

Convert from initial format and assign initial pagerank vector **v**

Move initial pageranks + graph to tmp file

Compute updated pageranks

Move new pageranks to tmp file for next iteration of loop

```
EDGEFILE = 'citeseer-graph.txt'
TMPFILE = 'tmp-pr-graph.txt'
RESET = 0.15
N = 10
```

```
def pageRankPlanner():

    p = Planner()

    def serialize(graphView):
        return \
            Format(graphView,
                   by=lambda(url,pagerank,outlinks):'\t'.join([url,'%g'%pagerank]+outlinks))

    # read in and create initial ranked graph
    p.edges = ReadLines(EDGEFILE) | Map(by=lambda line:line.strip().split(' '))
    p.initGraph = Group(p.edges, by=lambda (src,dst):src, retaining=lambda(src,dst):dst)
    p.initRankedGraph = Map(p.initGraph, by=lambda (url,outlinks):(url,1.0,outlinks))
    p.serializedInitRankedGraph = serialize(p.initRankedGraph)

    # one step of the update, reading the last iteration from a temp file
    p.prevGraph = \
        ReadLines(TMPFILE) \
        | Map(by=lambda line:line.strip().split("\t")) \
        | Map(by=lambda parts:(parts[0],float(parts[1]),parts[2:]))
    p.outboundPageRankMessages =  \
        FlatMap(p.prevGraph,
                by=lambda (url,pagerank,outlinks):
                map(lambda dst:(dst,pagerank/len(outlinks)), outlinks))
    p.newPageRank = \
        Group(p.outboundPageRankMessages,
              by=lambda (dst,deltaPageRank):dst,
              retaining=lambda (dst,deltaPageRank):deltaPageRank,
              reducingTo=ReduceTo(lambda:(RESET), lambda accum,delta:accum + (1-RESET)*delta))
    p.newRankedGraph = \
        Join( Jin(p.prevGraph, by=lambda (url,pagerank,outlinks):url),
              Jin(p.newPageRank, by=lambda (dst,newPageRank):dst)) \
        | Map(by=lambda((url,oldPageRank,outlinks),(url_,newPageRank)):(url,newPageRank,outlinks))
    p.serializedRankedGraph = serialize(p.newRankedGraph)

    p.setup()
    return p
```

row in initGraph: (i, [j1,….,jd])

lots and lots of i/o happening here…

```
def pageRankPlanner():

    p = Planner()

    def serialize(graphView):
        return \
            Format(graphView,
                   by=lambda(url,page

    # read in and create initial rank
    p.edges = ReadLines(EDGEFILE) | M
    p.initGraph = Group(p.edges, by=l
    p.initRankedGraph = Map(p.initGra
    p.serializedInitRankedGraph = ser

    # one step of the update, reading the last iteration from a temp file
    p.prevGraph = \
        ReadLines(TMPFILE) \
        | Map(by=lambda line:line.strip().split("\t")) \
        | Map(by=lambda parts:(parts[0],float(parts[1]),parts[2:]))
    p.outboundPageRankMessages =  \
        FlatMap(p.prevGraph,
                by=lambda (url,pagerank,outlinks):
                map(lambda dst:(dst,pagerank/len(outlinks)), outlinks))
    p.newPageRank = \
        Group(p.outboundPageRankMessages,
              by=lambda (dst,deltaPageRank):dst,
              retaining=lambda (dst,deltaPageRank):deltaPageRank,
              reducingTo=ReduceTo(lambda:(RESET), lambda accum,delta:accum + (1-RESET)*delta))
    p.newRankedGraph = \
        Join( Jin(p.prevGraph, by=lambda (url,pagerank,outlinks):url),
              Jin(p.newPageRank, by=lambda (dst,newPageRank):dst)) \
        | Map(by=lambda((url,oldPageRank,outlinks),(url_,newPageRank)):(url,newPageRank,outlinks))
    p.serializedRankedGraph = serialize(p.newRankedGraph)

    p.setup()
    return p
```

```
#create the initial graph w pagerank
planner = pageRankPlanner()
v0 = planner.getView('serializedInitRankedGraph')
v0.storagePlan().execute(planner)
print '>>> moving initial pageranks to',TMPFILE
os.rename(v0.storedFile(), TMPFILE)

for i in range(N):
    print '>>> pagerank iteration',i
    vi = planner.getView('serializedRankedGraph')
    vi.storagePlan().execute(planner)
    print '>>> moving round',i,'pageranks to',TMPFILE
    os.rename(vi.storedFile(), TMPFILE)
```

note: there is lots of i/o happening here…

Julien Le Dem - Yahoo

```
previous_pagerank =
    LOAD '$docs_in'
    USING PigStorage('\t')
    AS ( url: chararray, pagerank: float, links:{ link: ( url: chararray ) } );

outbound_pagerank =
    FOREACH previous_pagerank
    GENERATE
        pagerank / COUNT ( links ) AS pagerank,
        FLATTEN ( links ) AS to_url;

new_pagerank =
    FOREACH
        ( COGROUP outbound_pagerank BY to_url, previous_pagerank BY url INNER )
    GENERATE
        group AS url,
        ( 1 - $d ) + $d * SUM ( outbound_pagerank.pagerank ) AS pagerank,
        FLATTEN ( previous_pagerank.links ) AS links;

STORE new_pagerank
    INTO '$docs_out'
    USING PigStorage('\t');
```

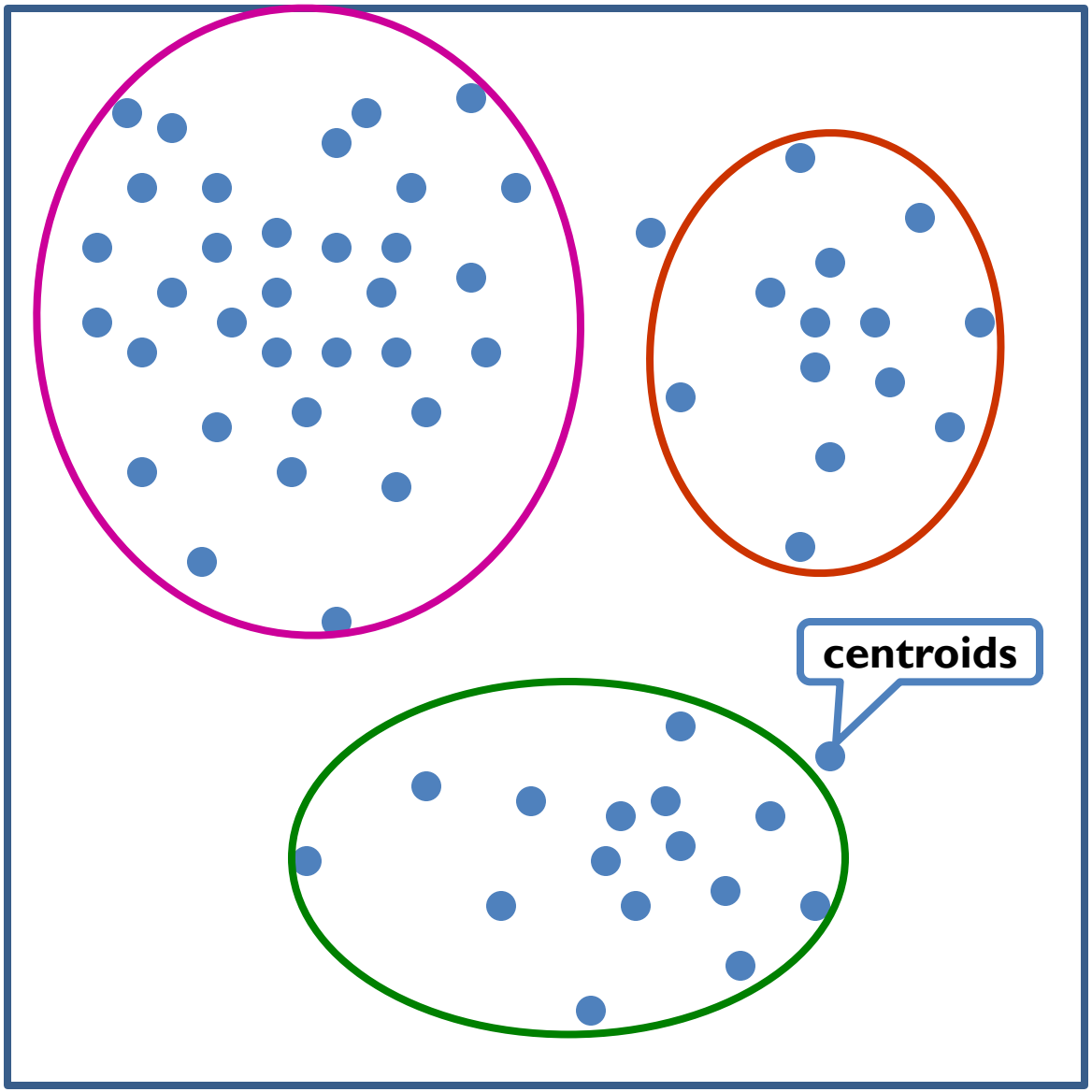
lots of i/o happening here…

An example from Ron Bekkerman of an iterative dataflow computation

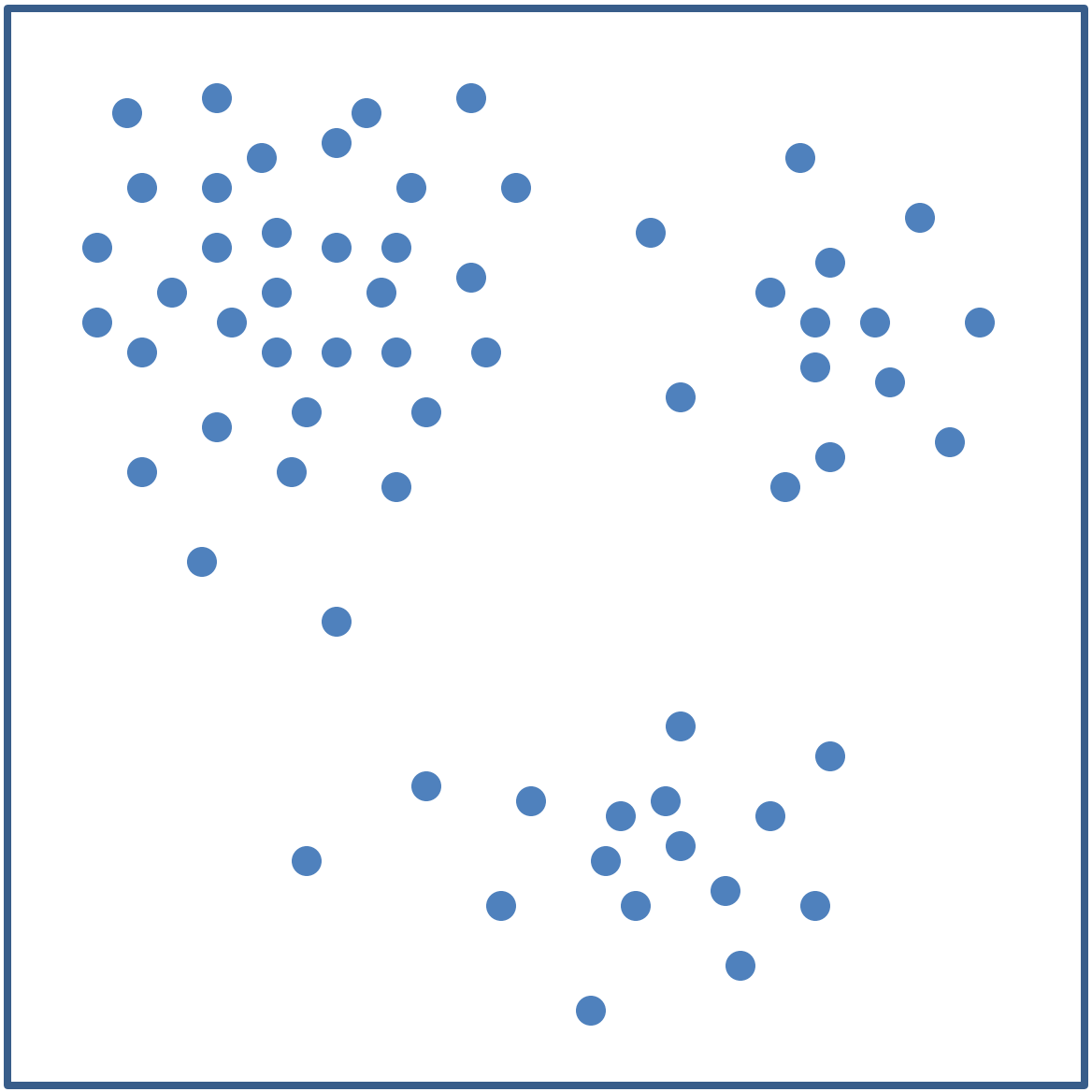
Example: *k*-means clustering

- An EM-like algorithm:
- Initialize k cluster centroids
- E-step: associate each data instance with the closest centroid
  - Find expected values of cluster assignments given the data and centroids
- M-step: recalculate centroids as an average of the associated data instances
  - Find new centroids that maximize that expectation

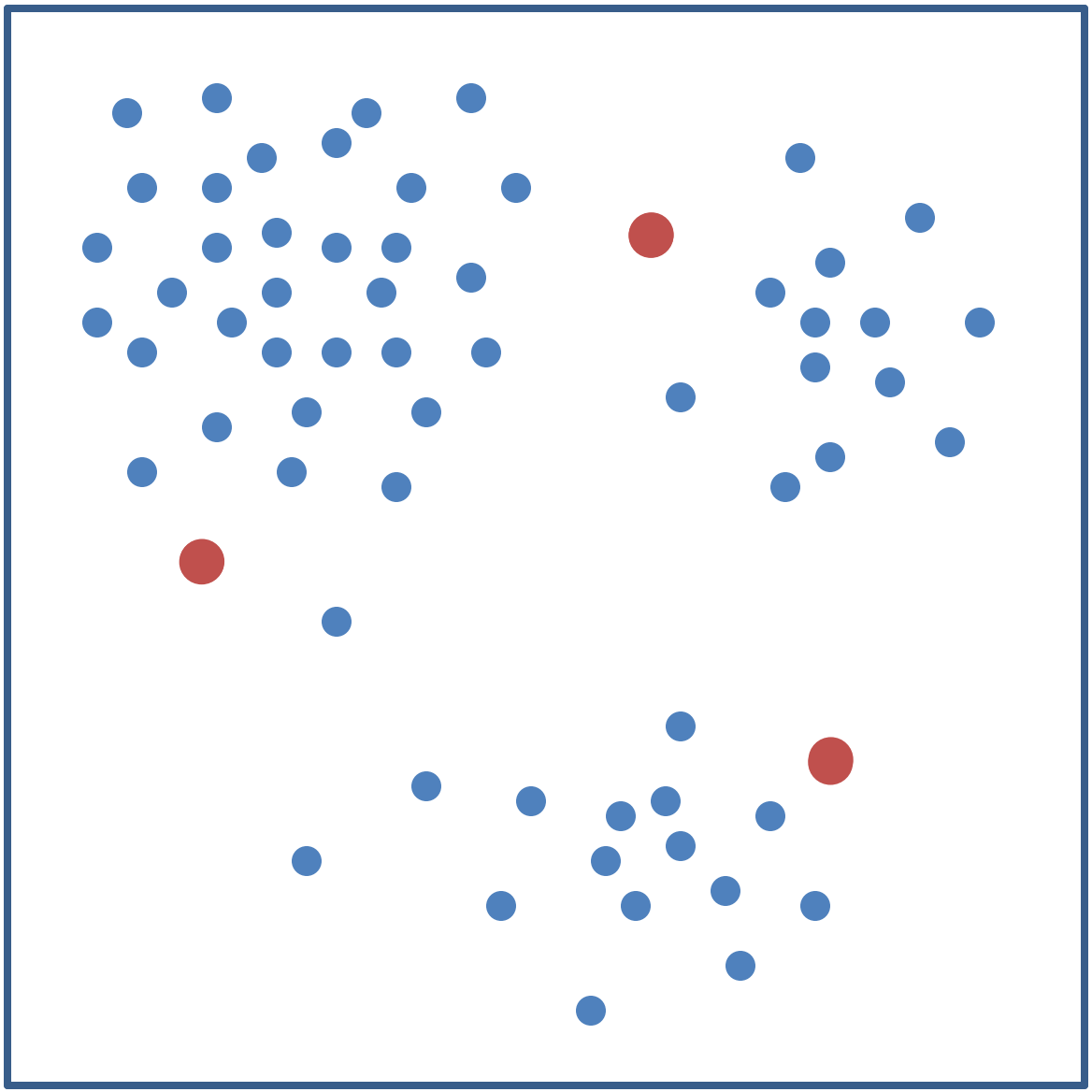
k-means Clustering



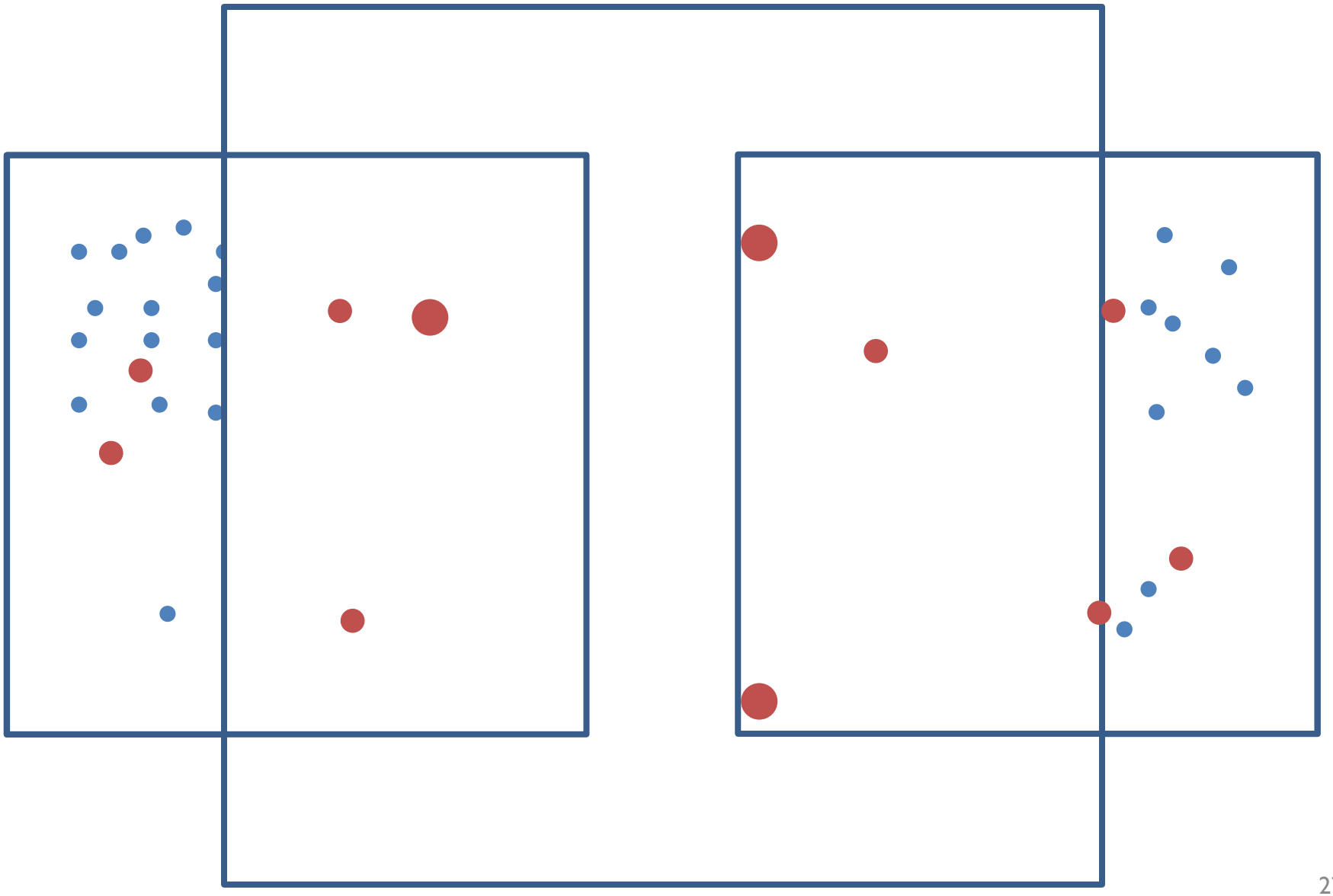
Parallelizing *k*-means



Parallelizing *k*-means



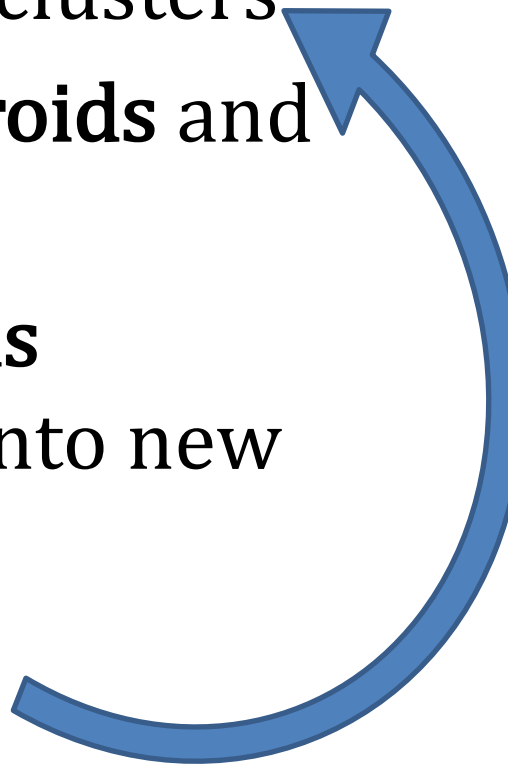
Parallelizing *k*-means



k-means on MapReduce

Panda et al, Chapter 2

- Mappers read data portions and centroids
- Mappers **assign data instances** to clusters
- Mappers **compute new local centroids** and local cluster sizes
- Reducers **aggregate local centroids** (weighted by local cluster sizes) into new global centroids
- Reducers **write the new centroids**



k-means in Apache Pig: input data

- Assume we need to cluster documents
  - Stored in a 3-column table D:

Document	Word	Count
doc1	Carnegie	2
doc1	Mellon	2

- Initial centroids are k randomly chosen docs
  - Stored in table C in the same format as above

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, i_d * i_c **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
*DOT_* ... *dXc*;

SQR
SQR_g
*LEN_* ... n_c;

*DOT_*
SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, *dXc* / len_c;

$$c_d = \arg\max_c \frac{\sum_{w \in d} i_d^w \cdot i_c^w}{\sqrt{\sum_{w \in c} \left(i_c^w\right)^2}}$$

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, i_d * i_c **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
*DOT_* ... *dXc*;

SQR
SQR_g
*LEN_* ... n_c;

*DOT_*
SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, *dXc* / len_c;

$$c_d = \arg\max_c \frac{\sum_{w \in d} i_d^w \cdot i_c^w}{\sqrt{\sum_{w \in c} \left(i_c^w\right)^2}}$$

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, i_d * i_c **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
*DOT_* dXc;

SQR
SQR_g
*LEN_* n_c;

*DOT_*
SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, dXc / l_c;

$$c_d = \arg\max_c \frac{\sum_{w \in d} i_d^w \cdot i_c^w}{\sqrt{\sum_{w \in c} \left(i_c^w\right)^2}}$$

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, i_d * i_c **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
*DOT_* ... dXc;

SQR
SQR_g
*LEN_* ... n_c;

*DOT_*
SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, *dXc* / *len* ;

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

$$c_d = \arg\max_c \frac{\sum_{w \in d} i_d^w \cdot i_c^w}{\sqrt{\sum_{w \in c} \left(i_c^w\right)^2}}$$

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, i_d * i_c **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
*DOT_*
SQR
SQR_g
*LEN_*
*DOT_*

$$c_d = \arg\max_c \frac{\sum_{w \in d} i_d^w \cdot i_c^w}{\sqrt{\sum_{w \in c} \left(i_c^w\right)^2}}$$

dXc;
n_c;

SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, *dXc* / len_c;

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

k-means in Apache Pig: E-step

D_C = **JOIN** *C* **BY** *w*, *D* **BY** *w*;
PROD = **FOREACH** *D_C* **GENERATE** *d*, *c*, $i_d * i_c$ **AS** $i_d i_c$;

$PROD_g$ = **GROUP** *PROD* **BY** (*d*, *c*);
DOT_PROD = **FOREACH** $PROD_g$ **GENERATE** *d*, *c*, SUM($i_d i_c$) **AS** *d*X*c*;

SQR = **FOREACH** *C* **GENERATE** *c*, $i_c * i_c$ **AS** i_c^2;
SQR_g = **GROUP** *SQR* **BY** c;
LEN_C = **FOREACH** SQR_g **GENERATE** *c*, SQRT(SUM(i_c^2)) **AS** len_c;

DOT_LEN = **JOIN** *LEN_C* **BY** *c*, *DOT_PROD* **BY** *c*;
SIM = **FOREACH** *DOT_LEN* **GENERATE** *d*, *c*, *d*X*c* / len_c;

document d, cluster c similarities

SIM_g = **GROUP** *SIM* **BY** *d*;
CLUSTERS = **FOREACH** SIM_g **GENERATE** TOP(1, 2, *SIM*);

cluster assignments: d→closest c

k-means in Apache Pig: M-step

D_C_W = **JOIN** *CLUSTERS* **BY** *d*, *D* **BY** *d*;

D_C_W$_g$ = **GROUP** *D_C_W* **BY** (*c*, *w*);
SUMS = **FOREACH** *D_C_W*$_g$ **GENERATE** *c*, *w*, SUM(i_d) **AS** *sum*;
add up documents in each cluster

D_C_W$_{gg}$ = **GROUP** *D_C_W* **BY** *c*;
SIZES = **FOREACH** *D_C_W*$_{gg}$ **GENERATE** *c*, COUNT(*D_C_W*) **AS** *size*;
figure out cluster size

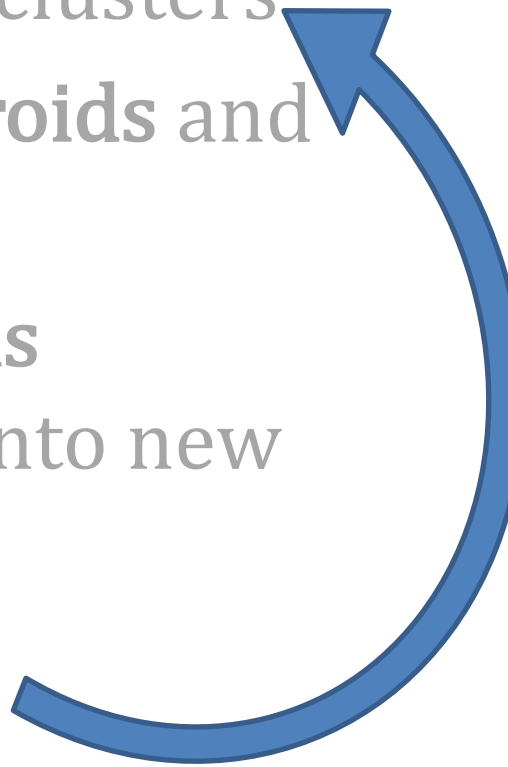
SUMS_SIZES = **JOIN** *SIZES* **BY** *c*, *SUMS* **BY** *c*;
C = **FOREACH** *SUMS_SIZES* **GENERATE** *c*, *w*, *sum* / *size* **AS** i_c ;
figure out weighted average of docs in each cluster

Finally - embed in Java (or Python or ….) to do the looping

Data is read, and model is written, with every iteration

Panda et al, Chapter 2

- Mappers read data portions and centroids
- Mappers **assign data instances** to clusters
- Mappers **compute new local centroids** and local cluster sizes
- Reducers **aggregate local centroids** (weighted by local cluster sizes) into new global centroids
- Reducers **write the new centroids**



Spark: Another Dataflow Language

Spark

- Hadoop: Too much typing
  - programs are not concise
- Hadoop: Too low level
  - missing abstractions
  - hard to specify a workflow
- Pig, Guinea Pig, … address these problems: also Spark
- Not well suited to iterative operations
  - E.g., PageRank, E/M, k-means clustering, …
  - Spark lowers cost of repeated reads

Set of concise dataflow operations ("transformation")

Dataflow operations are embedded in an API together with "actions"

Spark: Sharded files are replaced by "RDDs" – resilient distributed datasets.
RDDs can be cached in *cluster* memory and recreated to recover from error

Spark examples

spark is a *spark context* object

```
text_file = spark.textFile("hdfs://...")
errors = text_file.filter(lambda line: "ERROR" in line)
# Count all the errors
errors.count()
# Count errors mentioning MySQL
errors.filter(lambda line: "MySQL" in line).count()
# Fetch the MySQL errors as an array of strings
errors.filter(lambda line: "MySQL" in line).collect()
```

Spark examples

```
text_file = spark.textFile("hdf
errors = text_file.filter(
# Count all the errors
errors.count()
# Count errors mentioning MySQL
errors.filter(lambda line: "MySQL" in line).count()
# Fetch the MySQL errors as an array of strings
errors.filter(lambda line: "MySQL" in line).collect()
```

errors is a *transformation*, and thus a (that exp do s

count() is an *action*: it will actually execute the plan for **errors** and return a value.

everything is **sharded**, like in Hadoop and GuineaPig

errors.filter() is a *transformation*

collect() is an *action*

Spark examples

everything is **sharded** … and the shards are stored in *memory* of worker machines not local *disk* (if possible)

```
text_file = spark.textFile("hdfs://...")
errors = text_file.filter(lambda line: "ERROR" in line)
errors.cache()  # modify errors to be stored in cluster memory
errors.count()
# Count errors mentioning MySQL
errors.filter(lambda line: "MySQL" in line).count()
# Fetch the MySQL errors as an array of strings
errors.filter(lambda line: "MySQL" in line).collect()
```

subsequent actions will be much faster

You can also **persist()** an RDD on disk, which is like marking it as opts(stored=True) in GuineaPig. Spark's *not* smart about persisting data.

Spark examples

everything is **sharded** … and the shards are stored in *memory* of worker machines not local *disk* (if possible)

```
text_file = spark.textFile("hdfs://...")
errors = text_file.filter(lambda line: "
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errors.count()
# Count errors mentioning MySQL
errors.filter(lambda line: "MySQL" in li
# Fetch the MySQL errors as an array of st    gs
errors.filter(lambda line: "MySQL" in lin    .collect()
```

persist-on-disk works because the RDD is *read-only* (immutable)

You can also **persist()** an RDD on disk, which is like marking it as opts(stored=True) in GuineaPig. Spark's *not* smart about persisting data.

Spark examples: wordcount

```
text_file = spark.textFile("hdfs://...")
counts = text_file.flatMap(lambda line: line.split(" ")) \
             .map(lambda word: (word, 1)) \
             .reduceByKey(lambda a, b: a + b)
counts.saveAsTextFile("hdfs://...")
```

the action

transformation on (key,value) pairs , which are special

Spark examples: batch logistic regression

```
points = spark.textFile(...).map(parsePoint).cache()
w = numpy.random.ranf(size = D) # current separating plane
for i in range(ITERATIONS):
    gradient = points.map(
        lambda p: (1 / (1 + exp(-p.y*(w.dot(p.x)))) - 1) * p.y * p.x
    ).reduce(lambda a, b: a + b)
    w -= gradient
print "Final separating plane: %s" % w
```

reduce is an action – it produces a numpy vector

p.x and **w** are *vectors*, from the numpy package. Python overloads operations like * and + for vectors.

Spark examples: batch logistic regression

```
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    gradient = points.map(
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    ).reduce(lambda a, b: a + b)
    w -= gradient
print "Final separating plane: %s" % w
```

Important note: numpy vectors/matrices are not just "syntactic sugar".

- They are *much more compact* than something like a list of python floats.
- numpy operations like **dot, *, +** are calls to *optimized C code*
- a little python logic around a lot of numpy calls is pretty efficient

Spark examples: batch logistic regression

```
points = spark.textFile(...).map(parsePoint).cache()
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    gradient = points.map(
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    ).reduce(lambda a, b: a + b)
    w -= gradient
print "Final separating plane: %s" % w
```

So: python builds a *closure* – code including the *current value* of **w** – and Spark ships it off to each worker. So **w** is *copied*, and must be *read-only*.

w is defined *outside* the lambda function, but used *inside* it

Spark examples: batch logistic regression

```
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    ).reduce(lambda a, b: a + b)
    w -= gradient
print "Final separating plane: %s" % w
```
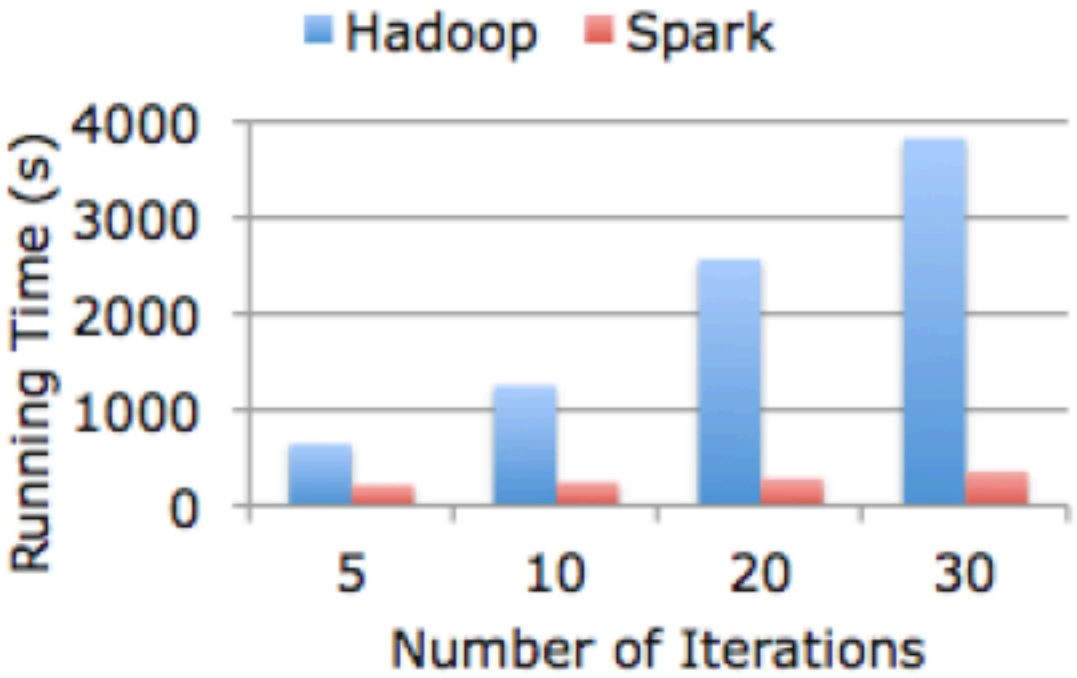
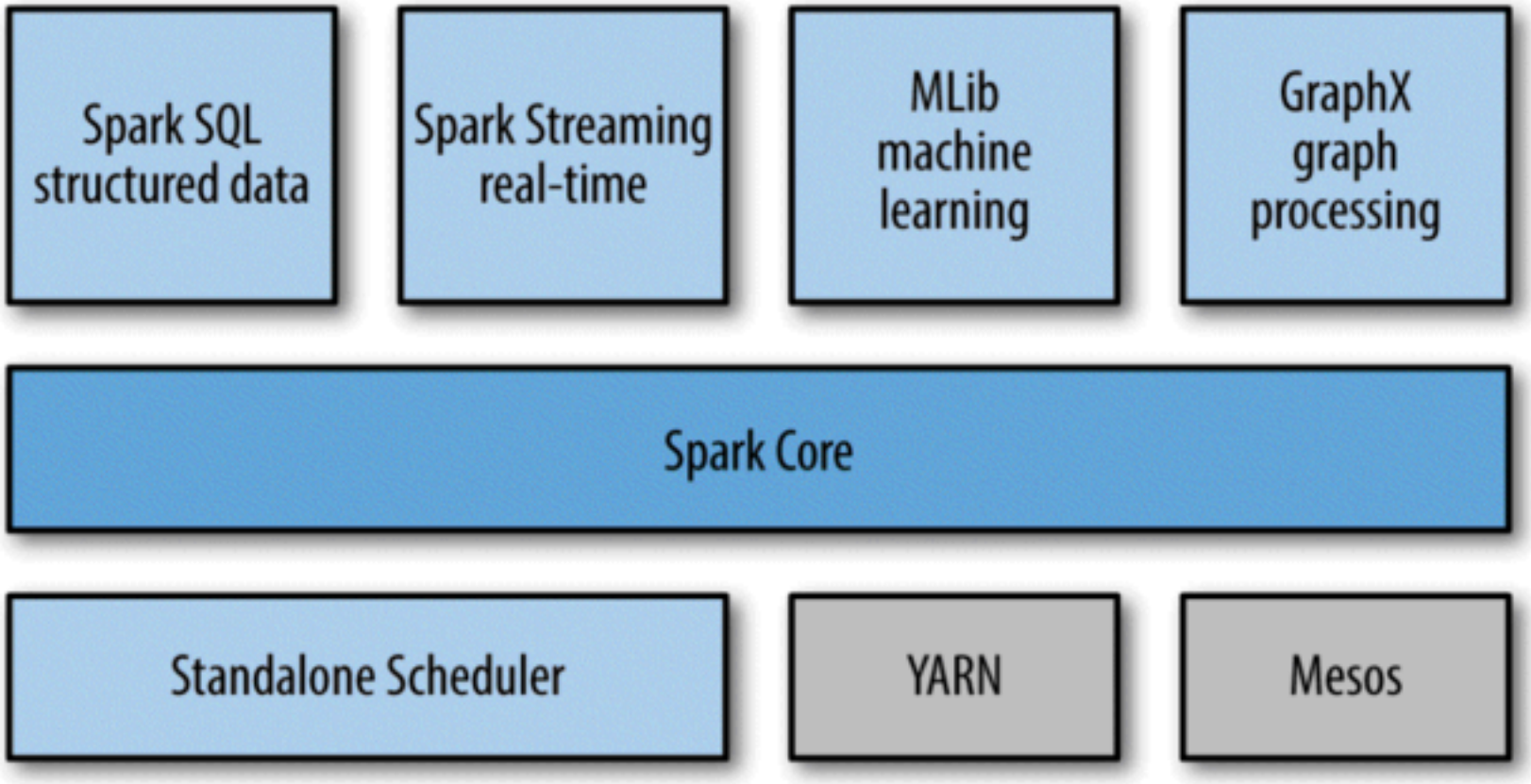

dataset of points is cached in cluster memory to reduce i/o

Spark logistic regression example

The graph below compares the performance of this Spark program against a Hadoop implementation on 30 GB of data on an 80-core cluster, showing the benefit of in-memory caching:



Spark


Spark SQL
structured data
Spark Streaming
real-time
MLib
machine
learning
GraphX
graph
processing
Spark Core
Standalone Scheduler
YARN
Mesos