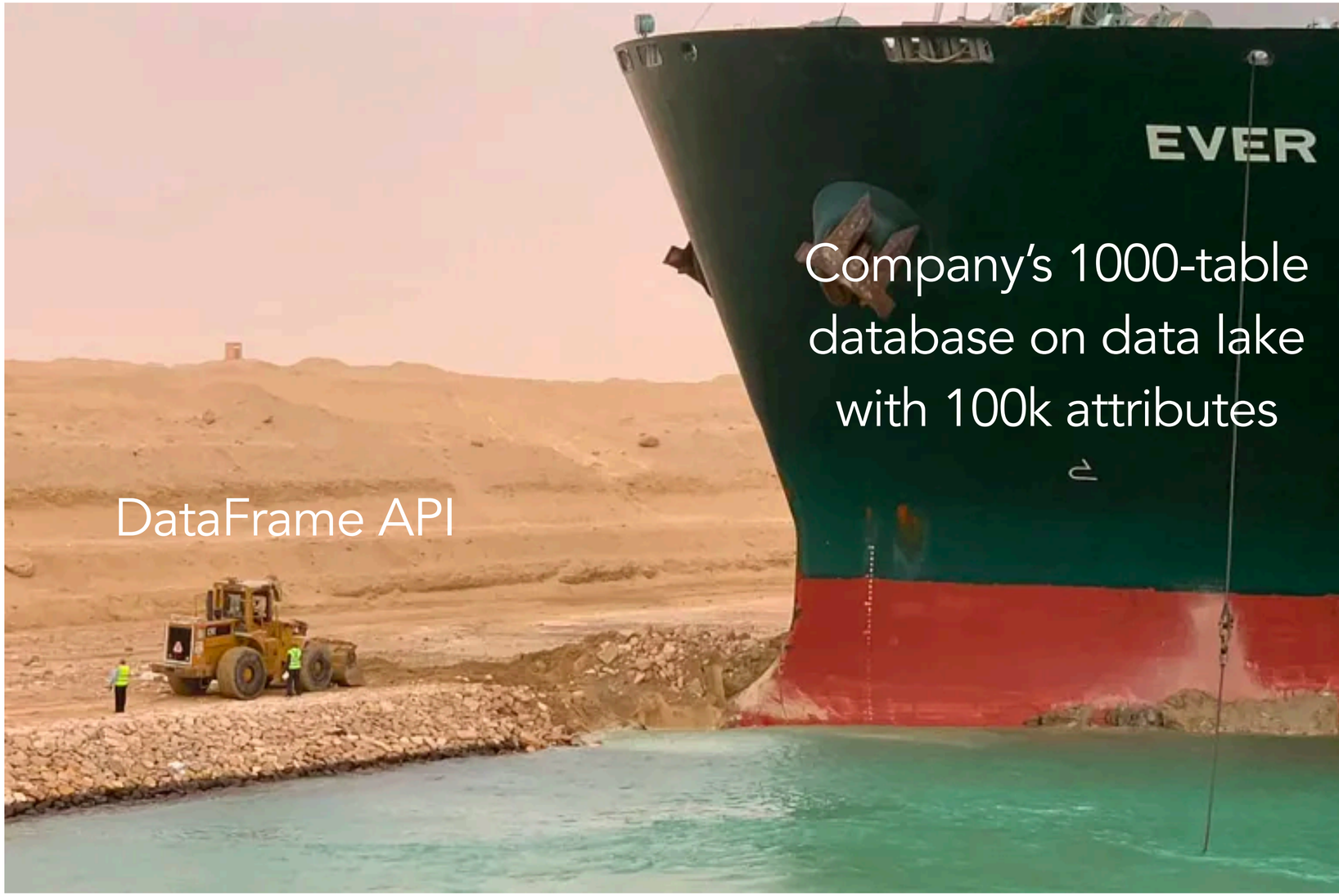
DSC 204a Scalable Data Systems

- Haojian Jin



Meme idea credit: https://datasystemsfun.tumblr.com/

Where are we in the class?

Foundations of Data Systems (2 weeks)

- Digital representation of Data → Computer Organization → Memory hierarchy → Process → Storage

Scaling Distributed Systems (3 weeks)

- Cloud → Network → Distributed storage → Parallelism → Partition and replication

Data Processing and Programming model (5 weeks)

- Data Models evolution → Data encoding evolution → IO & Unix Pipes → Batch processing (MapReduce) → **Stream processing (Spark)**

Today’s topic: Stream Processing

- Overview
-

Which program performs better? Program 1

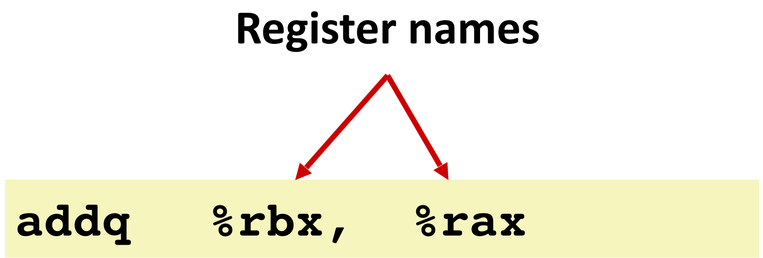
```
void add(int n, float* A, float* B, float* C){
  for (int i=0; i<n; i++)
    C[i] = A[i] + B[i];
}

void mul(int n, float* A, float* B, float* C) {
  for (int i=0; i<n; i++)
    C[i] = A[i] * B[i];
}

float* A, *B, *C, *D, *E, *tmp1, *tmp2;
// assume arrays are allocated here
// compute E = D + ((A + B) * C)
add(n, A, B, tmp1);
mul(n, tmp1, C, tmp2);
add(n, tmp2, D, E);
```

Two loads, one store per math op
(arithmetic intensity = 1/3)

Two loads, one store per math op
(arithmetic intensity = 1/3)

Overall arithmetic intensity = 1/3

Recall: Instruction



Basics of Processors

Q: *How does a processor execute machine code?*

- Types of ISA commands to manipulate register contents:
  - **Memory access: load** (copy bytes from a DRAM address to register); **store** (reverse); put constant
  - **Arithmetic & logic** on data items in registers: add/multiply/etc.; bitwise ops; compare, etc.; handled by ALU
  - **Control flow** (branch, call, etc.); handled by CU
- **Caches:** Small local memory to buffer instructions/data

If interested in more details: https://www.youtube.com/watch?v=cNN_tTXABUA

```
80483b5:    89 e5                   mov    %esp,%ebp
80483b7:    83 e4 f0                and    $0xfffffff0,%esp
80483ba:    83 ec 20                sub    $0x20,%esp
80483bd:    c7 44 24 1c 00 00 00    movl   $0x0,0x1c(%esp)
80483c4:    00
80483c5:    eb 11                   jmp    80483d8 <main+0x24>
80483c7:    c7 04 24 b0 84 04 08    movl   $0x80484b0,(%esp)
80483ce:    e8 1d ff ff ff          call   80482f0 <puts@plt>
80483d3:    83 44 24 1c 01          addl   $0x1,0x1c(%esp)
80483d8:    83 7c 24 1c 09          cmpl   $0x9,0x1c(%esp)
80483dd:    7e e8                   jle    80483c7 <main+0x13>
80483df:    b8 00 00 00 00          mov    $0x0,%eax
80483e4:    c9                      leave
80483e5:    c3                      ret
80483e6:    90                      nop
80483e7:    90                      nop
80483e8:    90                      nop
80483e9:    90                      nop
```

Which program performs better? Program 2

```
float*  A,*B,  *C,  *D,  *E,  *tmp1,   *tmp2;
// assume  arrays are  allocated here
// computeE = D + ((A   + B)*  C)
add(n, A,B, tmp1);
mul(n, tmp1, C,tmp2);
add(n, tmp2, D,    E);



void    fused(int n, float*  A,float*  B, float*  C,float*  D,
float*  E){
   for   (int  i=0; i<n; i++)
      E[i]  = D[i]  + (A[i] + B[i]) *  C[i];
}
// computeE = D + (A+ B)*  C
fused(n,  A, B,   C,    D,    E);
```

Overall arithmetic intensity = 1/3

Four loads, one store per 3 math ops
arithmetic intensity = 3/5

Loop fusion!

A log of page views on the 418 web site

```
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_012.jpg HTTP/1.1" 200 20186 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Ma
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_029.jpg HTTP/1.1" 200 31979 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Ma
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_031.jpg HTTP/1.1" 200 8425 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Mac
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_035.jpg HTTP/1.1" 200 29266 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Ma
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_041.jpg HTTP/1.1" 200 32678 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Ma
- [05/Apr/2016:22:44:10 -0400] "GET /spring2016content/lectures/16_synchronization/thumbs/slide_042.jpg HTTP/1.1" 200 32585 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Ma
- - [05/Apr/2016:22:44:15 -0400] "GET /spring2016/lecture/snoopimpl/slide_042 HTTP/1.1" 200 3689 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_041" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWeb
- - [05/Apr/2016:22:44:15 -0400] "GET /spring2016content/lectures/12_snoopimpl/images/slide_042.jpg HTTP/1.1" 200 161338 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_042" "Mozilla/5.0 (Macintosh; Intel Ma
- - [05/Apr/2016:22:44:17 -0400] "GET /spring2016/lecture/snoopimpl/slide_041 HTTP/1.1" 200 3093 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_042" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWeb
- [05/Apr/2016:22:44:17 -0400] "GET /spring2016/lecture/synchronization/slide_020 HTTP/1.1" 200 3180 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWe
- - [05/Apr/2016:22:44:18 -0400] "GET /spring2016/keep_alive HTTP/1.1" 200 957 "http://15418.courses.cs.cmu.edu/spring2016/lecture/basicarch/slide_073" "Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko
- [05/Apr/2016:22:44:18 -0400] "GET /spring2016content/lectures/16_synchronization/images/slide_020.jpg HTTP/1.1" 200 174283 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintos

- [05/Apr/2016:22:44:18 -0400] "GET /spring2016content/profile_pictures/sidwad.jpg HTTP/1.1" 200 34712 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_1
- [05/Apr/2016:22:44:18 -0400] "GET /spring2016content/profile_pictures/TomoA.jpg HTTP/1.1" 200 40709 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11
- [05/Apr/2016:22:44:18 -0400] "GET /spring2016content/profile_pictures/eknight7.jpg HTTP/1.1" 200 3132 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_
- [05/Apr/2016:22:44:18 -0400] "GET /spring2016content/profile_pictures/thomasts.jpg HTTP/1.1" 200 42369 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10
- - [05/Apr/2016:22:44:18 -0400] "GET /spring2016/lecture/snoopimpl/slide_040 HTTP/1.1" 200 4985 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_041" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWeb
- - [05/Apr/2016:22:44:19 -0400] "GET /spring2016/lecture/snoopimpl/slide_039 HTTP/1.1" 200 3447 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_040" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWeb
- - [05/Apr/2016:22:44:19 -0400] "GET /spring2016/lecture/snoopimpl/slide_040 HTTP/1.1" 200 4985 "http://15418.courses.cs.cmu.edu/spring2016/lecture/snoopimpl/slide_039" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWeb
- [05/Apr/2016:22:44:21 -0400] "GET /spring2016/users/login HTTP/1.1" 200 2302 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization/slide_020" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.1
- [05/Apr/2016:22:44:26 -0400] "POST /spring2016/users/do_login HTTP/1.1" 302 1061 "http://15418.courses.cs.cmu.edu/spring2016/users/login" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.17 (KHTML, like Ge
- [05/Apr/2016:22:44:26 -0400] "GET /spring2016/ HTTP/1.1" 200 4767 "http://15418.courses.cs.cmu.edu/spring2016/users/login" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.17 (KHTML, like Gecko) Version/9.1
- [05/Apr/2016:22:44:26 -0400] "GET /spring2016content/profile_pictures/cmusam.jpg HTTP/1.1" 200 42983 "http://15418.courses.cs.cmu.edu/spring2016/" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.17 (KHTML,
- [05/Apr/2016:22:44:30 -0400] "GET /spring2016/lectures HTTP/1.1" 200 6322 "http://15418.courses.cs.cmu.edu/spring2016/" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.17 (KHTML, like Gecko) Version/9.1 Sa
- [05/Apr/2016:22:44:33 -0400] "GET /spring2016/lecture/synchronization HTTP/1.1" 200 2871 "http://15418.courses.cs.cmu.edu/spring2016/lectures" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/601.5.17 (KHTML, lik
- [05/Apr/2016:22:44:35 -0400] "GET /spring2013content/lectures/03_progmodels/images/slide_032.png HTTP/1.1" 304 189 "-" "Mozilla/5.0 (compatible; YandexImages/3.0; +http://yandex.com/bots)"
- [05/Apr/2016:22:44:38 -0400] "GET /spring2016/lecture/synchronization/slide_020 HTTP/1.1" 200 3852 "http://15418.courses.cs.cmu.edu/spring2016/lecture/synchronization" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWe
- [05/Apr/2016:22:45:00 -0400] "GET /spring2013/article/26 HTTP/1.1" 200 5900 "http://www.google.co.in/search?ie=UTF-8&q=split+transaction+bus&revid=112973050&sa=X&ved=0ahUKEwio0PfG_vjLAhVinIMKHQO5AdYQ1QIIBQ" "UCWEB/2.0 (Java;
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/js/15418_common.js HTTP/1.1" 200 425 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.218 U2/
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/jquery/timeago/jquery.timeago.js HTTP/1.1" 200 2026 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/jquery/cookie/jquery.cookie.js HTTP/1.1" 200 1189 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/date/date.js HTTP/1.1" 200 7628 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/codemirror-3.0/mode/markdown/markdown.js HTTP/1.1" 200 4018 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.3
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/google-code-prettify/prettify.js HTTP/1.1" 200 6379 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/jquery/tmpl/jquery.tmpl.min.js HTTP/1.1" 200 3155 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/css/main.css HTTP/1.1" 200 3368 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.218 U2/1.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/jquery/1.8.3/jquery.min.js HTTP/1.1" 200 33789 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 U
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/codemirror-3.0/lib/codemirror.css HTTP/1.1" 200 2319 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/google-code-prettify/prettify.css HTTP/1.1" 200 660 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/js/main.js HTTP/1.1" 200 1512 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.218 U2/1.0.0 M
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/third_party/codemirror-3.0/lib/codemirror.js HTTP/1.1" 200 47855 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013/assets/js/comments.js HTTP/1.1" 200 2413 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.218 U2/1.0
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013//assets/images/favicon/dragon.png HTTP/1.1" 200 3145 "-" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.218 U2/1.0.0 Mobile"
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013content/article_images/26_3.jpg HTTP/1.1" 200 28441 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013content/article_images/26_2.jpg HTTP/1.1" 200 25683 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013content/article_images/26_4.jpg HTTP/1.1" 200 38414 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/8.7.0.
- [05/Apr/2016:22:45:01 -0400] "GET /spring2013content/profile_pictures/lazyplus.jpg HTTP/1.1" 200 40708 "http://15418.courses.cs.cmu.edu/spring2013/article/26" "UCWEB/2.0 (Java; U; MIDP-2.0; Nokia203/20.37) U2/1.0.0 UCBrowser/
- - [05/Apr/2016:22:45:10 -0400] "GET /spring2016/keep_alive HTTP/1.1" 200 957 "http://15418.courses.cs.cmu.edu/spring2016/article/9" "Mozilla/5.0 (Windows NT 6.1; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623
- - [05/Apr/2016:22:46:31 -0400] "GET / HTTP/1.1" 302 564 "-" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623.110 Safari/537.36"
- - [05/Apr/2016:22:46:31 -0400] "GET /spring2016 HTTP/1.1" 301 584 "-" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623.110 Safari/537.36"
- - [05/Apr/2016:22:46:31 -0400] "GET /spring2016/ HTTP/1.1" 200 5254 "-" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623.110 Safari/537.36"
- [05/Apr/2016:22:46:40 -0400] "GET /spring2016/lecture/lockfree/slide_028 HTTP/1.1" 200 4008 "-" "Mozilla/5.0 (compatible; Googlebot/2.1; +http://www.google.com/bot.html)"
- - [05/Apr/2016:22:46:41 -0400] "GET /spring2016/keep_alive HTTP/1.1" 200 958 "http://15418.courses.cs.cmu.edu/spring2016/article/14" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWebKit/537.36 (KHTML, like Gecko) Chr
- [05/Apr/2016:22:46:51 -0400] "GET /spring2016/keep_alive HTTP/1.1" 200 999 "http://15418.courses.cs.cmu.edu/spring2016/article/14" "Mozilla/5.0 (Windows NT 6.1; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623.
- [05/Apr/2016:22:47:00 -0400] "GET /spring2014content/lectures/24_memory/images/slide_014.png HTTP/1.1" 304 190 "-" "Mozilla/5.0 (compatible; YandexImages/3.0; +http://yandex.com/bots)"
- [05/Apr/2016:22:47:25 -0400] "GET /spring2015/article/11 HTTP/1.1" 200 6180 "https://www.google.com/" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.2623.110 Safari/537.36"
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/jquery/timeago/jquery.timeago.js HTTP/1.1" 200 2026 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) App
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/jquery/1.8.3/jquery.min.js HTTP/1.1" 200 33788 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWeb
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/codemirror-3.0/lib/codemirror.css HTTP/1.1" 200 2319 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) Ap
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/google-code-prettify/prettify.css HTTP/1.1" 200 660 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) App
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- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/jquery/cookie/jquery.cookie.js HTTP/1.1" 200 1189 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) Apple
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/codemirror-3.0/lib/codemirror.js HTTP/1.1" 200 47854 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) Ap
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/codemirror-3.0/mode/markdown/markdown.js HTTP/1.1" 200 4017 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_1
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/third_party/google-code-prettify/prettify.js HTTP/1.1" 200 6378 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) App
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/js/main.js HTTP/1.1" 200 806 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/537.36 (KHTML, like Gecko)
- [05/Apr/2016:22:47:26 -0400] "GET /spring2015/assets/js/comments.js HTTP/1.1" 200 3779 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/537.36 (KHTML, like
- [05/Apr/2016:22:47:29 -0400] "GET /spring2015/assets/images/favicon/dragon.png HTTP/1.1" 200 3145 "http://15418.courses.cs.cmu.edu/spring2015/article/11" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_4) AppleWebKit/537.36 (KH
- - [05/Apr/2016:22:47:41 -0400] "GET /spring2015content/lectures/21_heterogeneity/thumbs/slide_037.png HTTP/1.1" 304 133 "-" "Mozilla/4.0 (compatible;)"
- [05/Apr/2016:22:48:50 -0400] "GET /spring2016content/article_images/3_.jpg HTTP/1.1" 200 65173 "https://www.google.com/" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_0) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/49.0.262
- [05/Apr/2016:22:49:09 -0400] "GET /spring2016/keep_alive HTTP/1.1" 200 1012 "http://15418.courses.cs.cmu.edu/spring2016/article/15" "Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_3) AppleWebKit/537.36 (KHTML, like Gecko) Chr
```
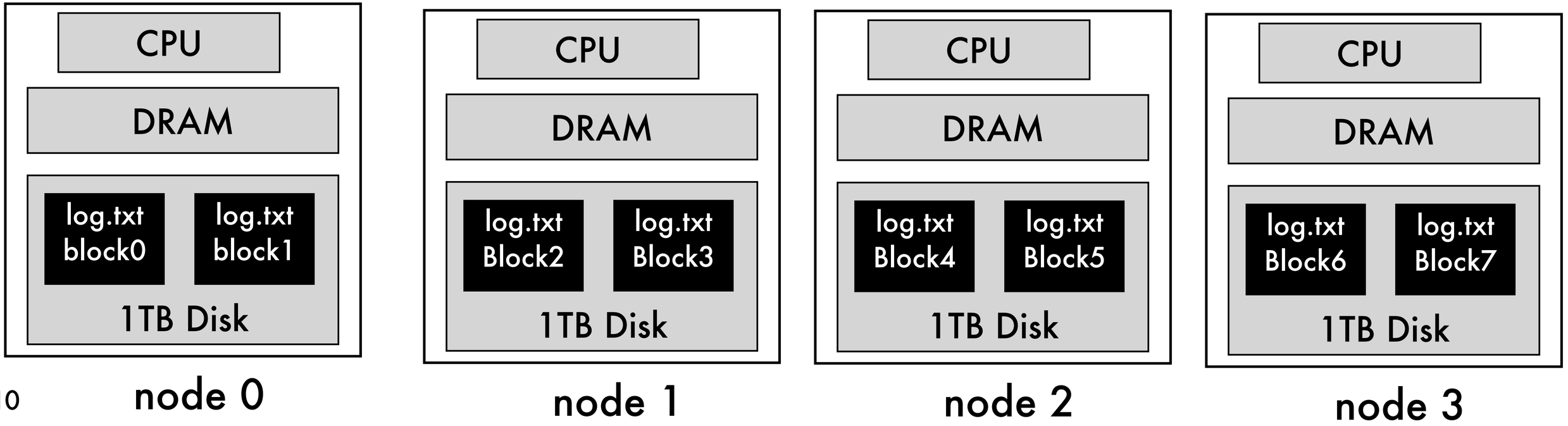

The log of page views gets quite large...

Assume log.txt is a large file, stored in a distributed file system, like HDFS
Below: cluster of 4 nodes,
each node with a 1 TB disk
Contents of log.txt are distributed evenly in blocks across the cluster



Example query:

"What type of mobile phone are all the visitors using?"

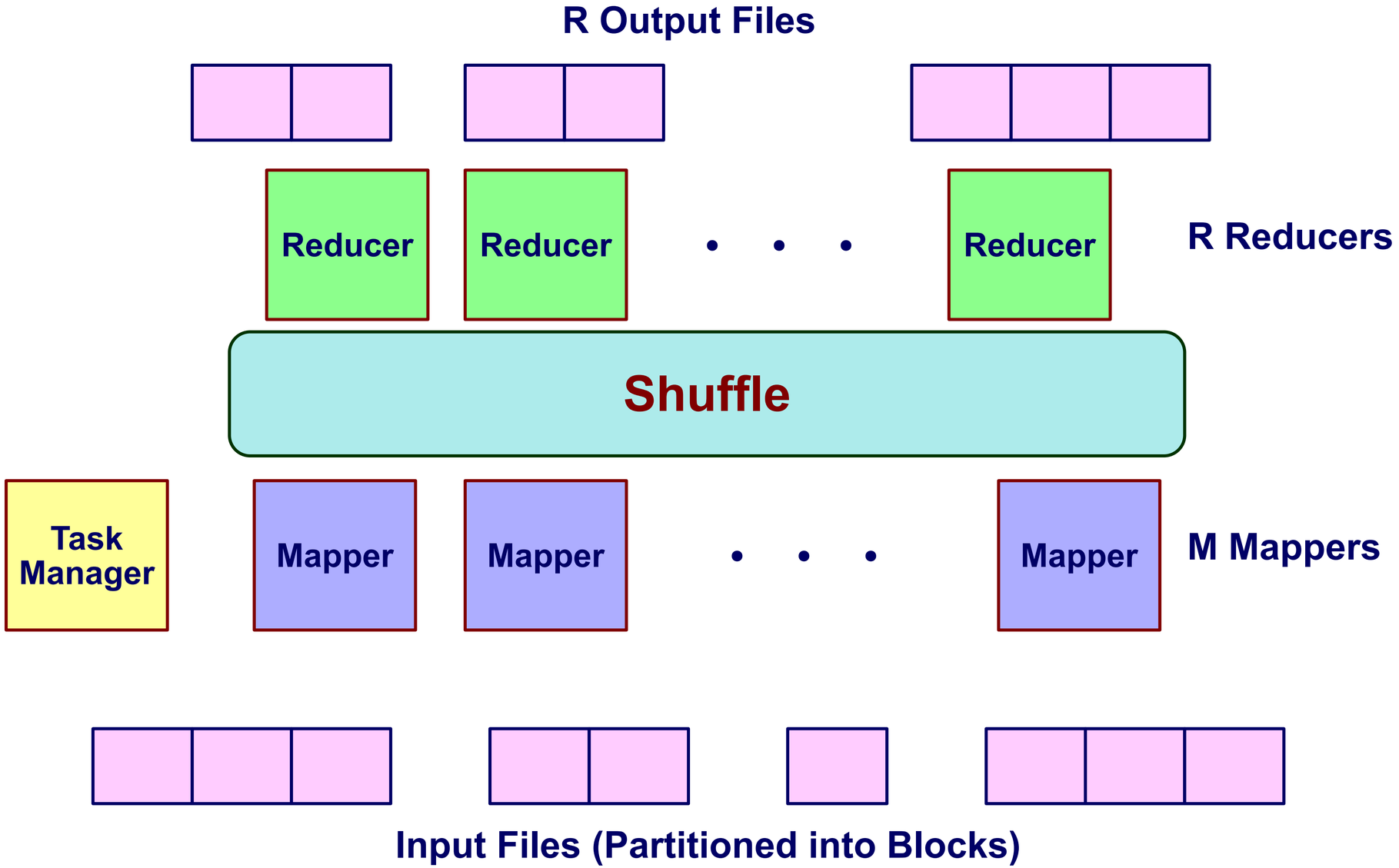
Using MapReduce

```
// called once per line in input file by runtime
// input: string (line of input file)
// output: adds (user_agent, 1) entry to list
void mapper(string line, multimap<string,string>& results) {
   string user_agent = parse_requester_user_agent(line);
   if (is_mobile_client(user_agent))
     results.add(user_agent, 1);
}

// called once per unique key (user_agent) in results
// values is a list of values associated with the given key
void reducer(string key, list<string> values, int& result) {
    int sum = 0;
    for (v in values)
       sum += v;
    result = sum;
}
```

LineByLineReader input("hdfs://log.txt");
Writer output("hdfs://...");
runMapReduceJob(mapper, reducer, input, output);

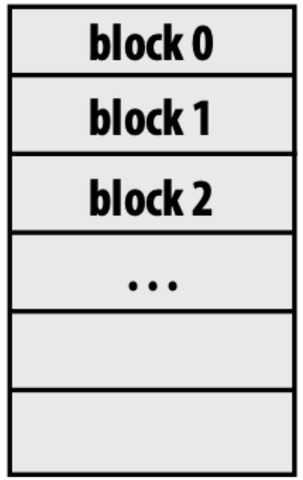
The code left computes the count of page views by each type of mobile phone.

How MapReduce Task Manager works?



How to assign work to nodes?

Idea 1: use work queue for list of input blocks to process Dynamic assignment: free node takes next available block



Idea 2: data distribution based assignment: Each node processes lines in blocks of input fle that are stored locally.

Exploit data locality: "move computation to the data":
- Run mapper jobs on nodes that contain input files

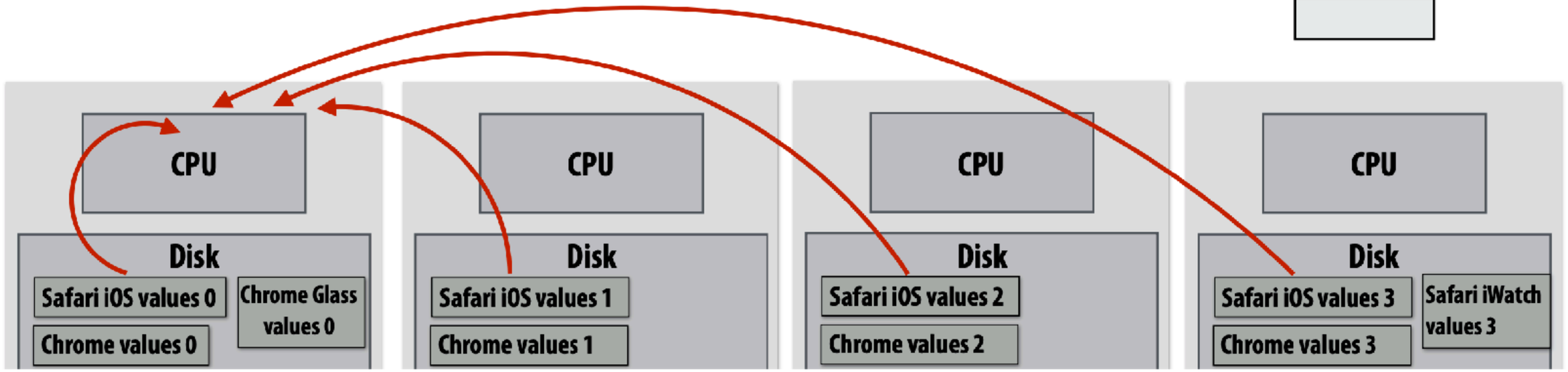
How to get all data for key onto the correct worker node?

Exploit data locality: "move computation to the data":
- Run reducer jobs on nodes that already have most of data for a certain key

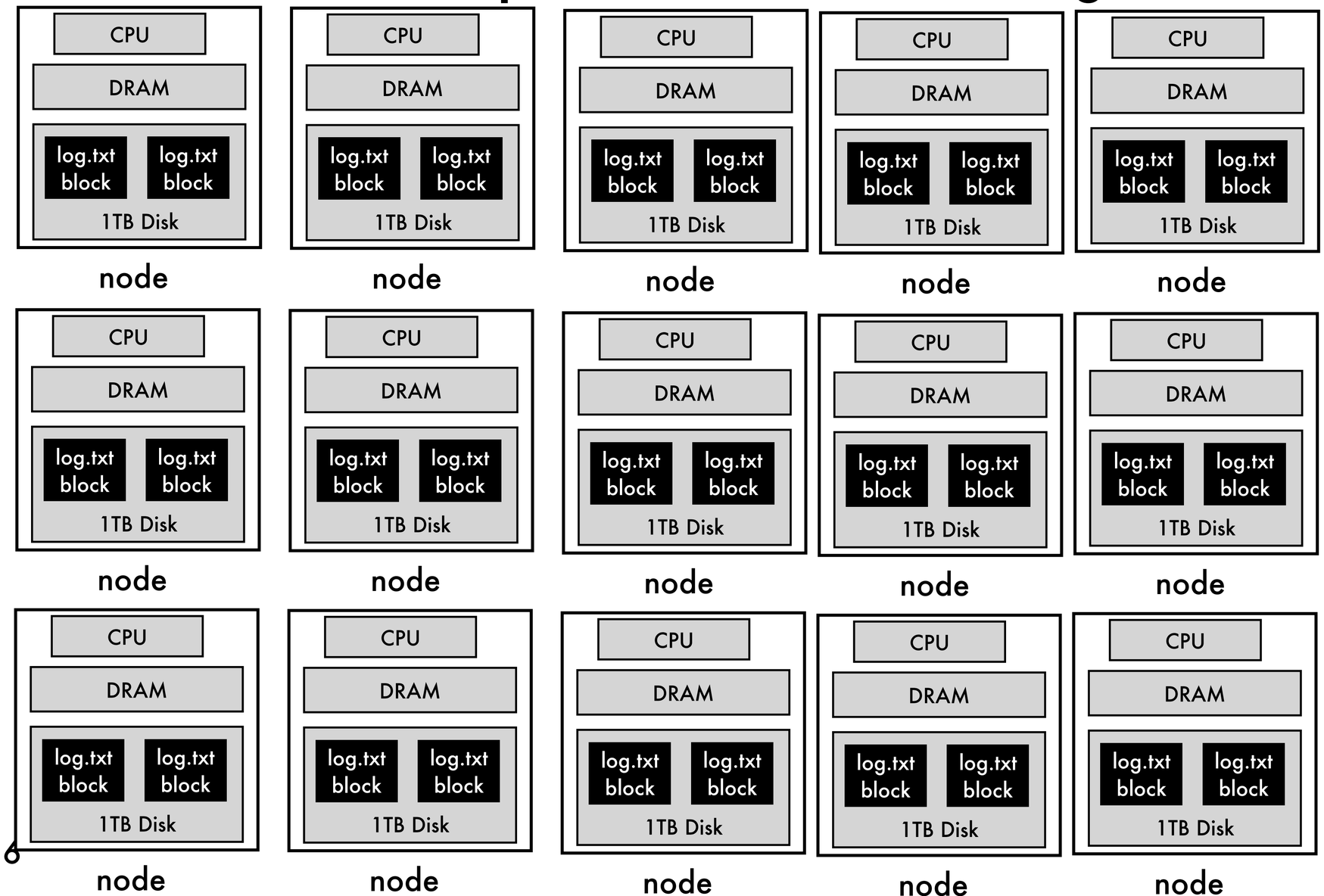
Example:
Assign Safari iOS to Node 0

Keys to reduce:
(generated by mapper):

Safari iOS
Chrome
Safari iWatch
Chrome Glass



Additional implementation challenges at scale



Nodes may fail during program execution

Some nodes may run slower than others (due to different amounts of work, heterogeneity in the cluster, etc..)

Other Job scheduler responsibilities

Handling node failures

- Scheduler detects job failures and reruns job on new machines
  - This is possible since inputs reside in persistent storage (distributed file system)
- Scheduler duplicates jobs on multiple machines (reduce overall processing latency incurred by node failures)

Handling slow machines

- Scheduler duplicates jobs on multiple machines

Problems of MapReduce

Permits only a very simple program structure Scheduler detects job failures and reruns job on new machines

- Programs must be structured as: map, followed by reduce by key
- Generalize structure to DAGs

Iterative algorithms must load from disk each iteration

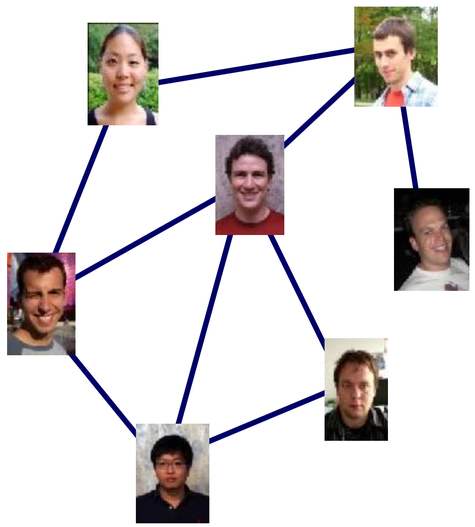
- e.g., pagerank

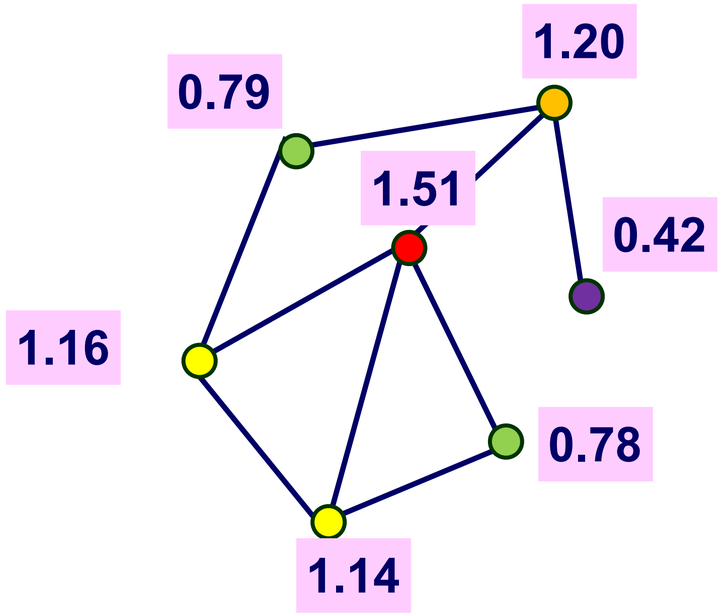
PageRank

PageRank Computation

- Larry Page & Sergey Brinn, 1998

Rank “Importance” of Web Pages





PageRank Computation

Initially

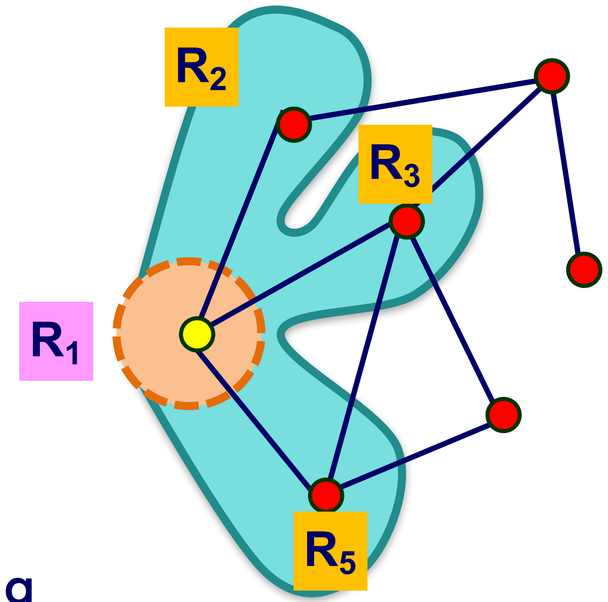
- Assign weight 1.0 to each page

Iteratively

- Select arbitrary node and update its value

Convergence

- Results unique, regardless of selection ordering



$$R_1 \leftarrow \quad 0.1 + 0.9 * (\tfrac{1}{2} R_2 + \tfrac{1}{4} R_3 + \tfrac{1}{3} R_5)$$

PageRank with Map/Reduce

$R_1 \leftarrow \quad 0.1 + 0.9 * (\frac{1}{2} R_2 + \frac{1}{4} R_3 + \frac{1}{3} R_5)$

Each Iteration: Update all nodes

- Map: Generate values to pass along each edge
  - Key value 1: (1, ½ R_2) (1, ¼ R_3) (1, ⅓ R_5)
  - Similar for all other keys
- Reduce: Combine edge values to get new rank
  - $R_1 \leftarrow \quad 0.1 + 0.9 * (\frac{1}{2} R_2 + \frac{1}{4} R_3 + \frac{1}{3} R_5)$
  - Similar for all other nodes

Iterative algorithms must load from disk each iteration

```
void pagerank_mapper(graphnode n, map<string,string> results) {
   float val = compute update value for n
   for (dst in outgoing links from n)
     results.add(dst.node, val);
}

void pagerank_reducer(graphnode n, list<float> values, float& result) {
    float sum = 0.0;
    for (v in values)
       sum += v;
    result = sum;
}

for (i = 0 to NUM_ITERATIONS) {
   input = load graph from last iteration
   output = file for this iteration output
   runMapReduceJob(pagerank_mapper, pagerank_reducer, result[i-1], result[i]);
}
```

in-memory, fault-tolerant distributed computing
http://spark.apache.org/

Goals

- Programming model for cluster-scale computations where there is signifcant reuse of intermediate datasets
  - Iterative machine learning and graph algorithms
  - Interactive data mining: load large dataset into aggregate memory of cluster and then perform multiple ad-hoc queries

- Don't want incur inefficiency of writing intermediates to persistent distributed file system (want to keep it in memory)
  - Challenge: efficiently implementing fault tolerance for large-scale distributed in-memory computations.

Fault tolerance for in-memory calculations

- Replicate all computations
  - Expensive solution: decreases peak throughput

- Checkpoint and rollback
  - Periodically save state of program to persistent storage
  - Restart from last checkpoint on node failure

- Maintain log of updates (commands and data)
  - High overhead for maintaining logs

Recall map-reduce solutions

- Checkpoints after each map/reduce step by writing results to fle system
- Scheduler's list of outstanding (but not yet complete) jobs is a log
- Functional structure of programs allows for restart at granularity of a single mapper or reducer invocation
  - (don't have to restart entire program)

Resilient distributed dataset (RDD)

Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

Matei Zaharia, Mosharaf Chowdhury, Tathagata Das, Ankur Dave, Justin Ma, Murphy McCauley, Michael J. Franklin, Scott Shenker, Ion Stoica
University of California, Berkeley

Abstract

We present Resilient Distributed Datasets (RDDs), a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner. RDDs are motivated by two types of applications that current computing frameworks handle inefficiently: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarse-grained transformations rather than fine-grained updates to shared state. However, we show that RDDs are expressive enough to capture a wide class of computations, including recent specialized programming models for iterative jobs, such as Pregel, and new applications that these models do not capture. We have implemented RDDs in a system called Spark, which we evaluate through a variety of user applications and benchmarks.

1 Introduction

Cluster computing frameworks like MapReduce [10] and Dryad [19] have been widely adopted for large-scale data analytics. These systems let users write parallel computations using a set of high-level operators, without having to worry about work distribution and fault tolerance.

Although current frameworks provide numerous abstractions for accessing a cluster's computational resources, they lack abstractions for leveraging distributed memory. This makes them inefficient for an important class of emerging applications: those that *reuse* intermediate results across multiple computations. Data reuse is common in many *iterative* machine learning and graph algorithms, including PageRank, K-means clustering, and logistic regression. Another compelling use case is *interactive* data mining, where a user runs multiple ad-hoc queries on the same subset of the data. Unfortunately, in most current frameworks, the only way to reuse data between computations (*e.g.*, between two MapReduce jobs) is to write it to an external stable storage system, which can dominate application execution times.

Recognizing this problem, researchers have developed specialized frameworks for some applications that require data reuse. For example, Pregel [22] is a system for iterative graph computations that keeps intermediate data in memory, while HaLoop [7] offers an iterative MapReduce interface. However, these frameworks only support specific computation patterns (*e.g.*, looping a series of MapReduce steps), and perform data sharing implicitly for these patterns. They do not provide abstractions for more general reuse, *e.g.*, to let a user load several datasets into memory and run ad-hoc queries across them.

In this paper, we propose a new abstraction called *resilient distributed datasets (RDDs)* that enables efficient data reuse in a broad range of applications. RDDs are fault-tolerant, parallel data structures that let users explicitly persist intermediate results in memory, control their partitioning to optimize data placement, and manipulate them using a rich set of operators.

The main challenge in designing RDDs is defining a programming interface that can provide fault tolerance *efficiently*. Existing abstractions for in-memory storage on clusters, such as distributed shared memory [24], key-value stores [25], databases, and Piccolo [27], offer an interface based on fine-grained updates to mutable state (*e.g.*, cells in a table). With this interface, the only ways to provide fault tolerance are to replicate the data across machines or to log updates across machines. Both approaches are expensive for data-intensive workloads, as they require copying large amounts of data over the cluster network, whose bandwidth is far lower than that of RAM, and they incur substantial storage overhead.

In contrast to these systems, RDDs provide an interface based on *coarse-grained* transformations (*e.g.*, map, filter and join) that apply the same operation to many data items. This allows them to efficiently provide fault tolerance by logging the transformations used to build a dataset (its *lineage*) rather than the actual data.[1] If a partition of an RDD is lost, the RDD has enough information about how it was derived from other RDDs to recompute

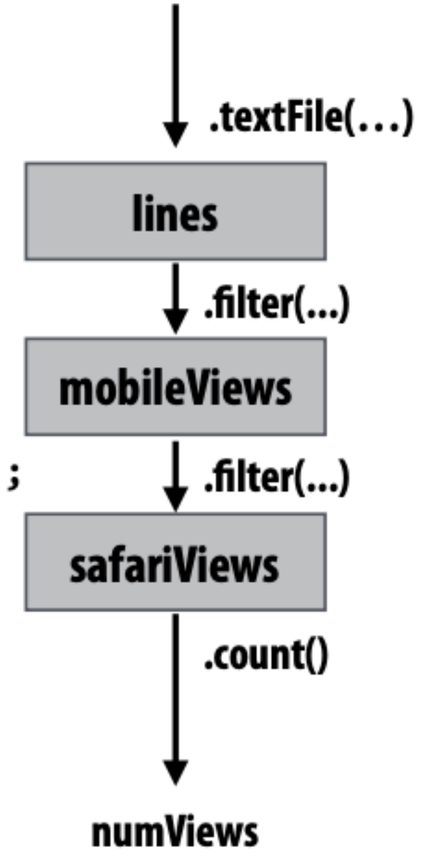
RDD: Spark's key programming abstraction:

- Read-only collection of records (immutable)
- RDDs can only be created by deterministic transformations on data in persistent storage or on existing RDDs
- Actions on RDDs return data to application

RDDs

```
// create RDD from file system data
var lines = spark.textFile("hdfs://15418log.txt");

// create RDD using filter() transformation on lines
var mobileViews = lines.filter((x: String) => isMobileClient(x));

// another filter() transformation
var safariViews = mobileViews.filter((x: String) => x.contains("Safari"));

// then count number of elements in RDD via count() action
var numViews = safariViews.count();
```

int

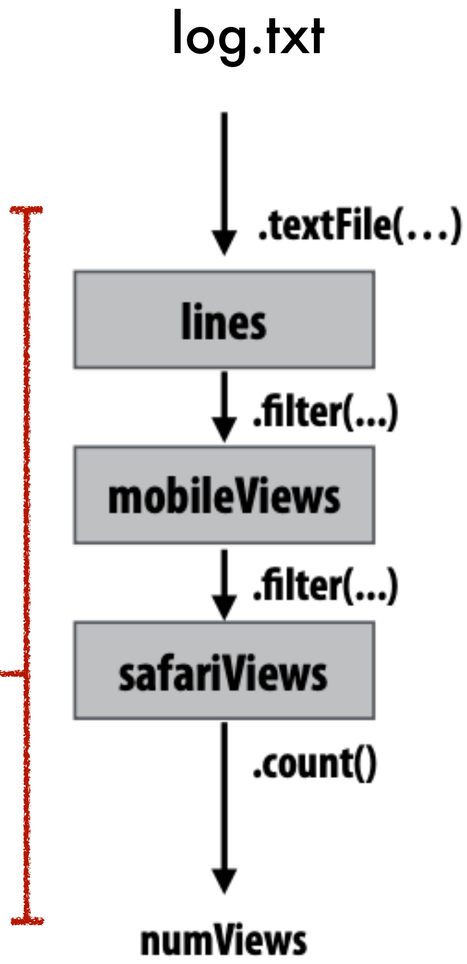


Repeating the map-reduce example

```
// 1. create RDD from file system data
// 2. create RDD with only lines from mobile clients
// 3. create RDD with elements of type (String,Int) from line string
// 4. group elements by key
// 5. call provided reduction function on all keys to count views
var perAgentCounts = spark.textFile("hdfs://log.txt")
                          .filter(x => isMobileClient(x))
                          .map(x => (parseUserAgent(x),1));
                          .reduceByKey((x,y) => x+y)
                          .collect();
```

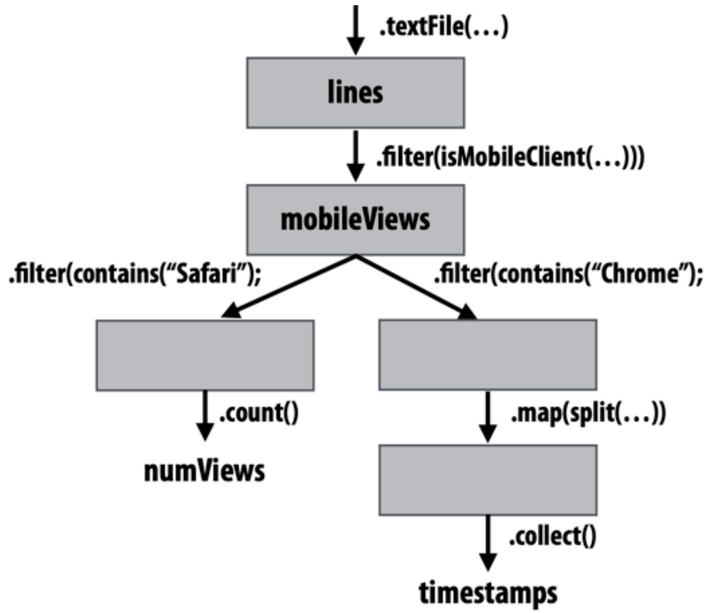
Array [String,int]

"Lineage": Sequence of RDD operations needed to compute output



Another Spark program

```
// create RDD from file system data
var lines = spark.textFile("hdfs://log.txt");

// create RDD using filter() transformation on lines
var mobileViews = lines.filter((x: String) => isMobileClient(x));

// instruct Spark runtime to try to keep mobileViews in memory
mobileViews.persist();

// create a new RDD by filtering mobileViews
// then count number of elements in new RDD via count() action
var numViews = mobileViews.filter(_.contains("Safari")).count();

// 1. create new RDD by filtering only Chrome views
// 2. for each element, split string and take timestamp of // page view
// 3. convert RDD to a scalar sequence (collect() action)
var timestamps = mobileViews.filter(_.contains("Chrome"))
                            .map(_.split(" ")(0))
                            .collect();
```



RDD transformations and actions

Transformations: (data parallel operators taking an input RDD to a new RDD)

$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	RDD[T] ⇒ RDD[U]
$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	RDD[T] ⇒ RDD[T]
$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	RDD[T] ⇒ RDD[U]
$sample(fraction : \mathrm{Float})$	:	RDD[T] ⇒ RDD[T] (Deterministic sampling)
$groupByKey()$	:	RDD[(K, V)] ⇒ RDD[(K, Seq[V])]
$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
$union()$	:	(RDD[T], RDD[T]) ⇒ RDD[T]
$join()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (V, W))]
$cogroup()$	:	(RDD[(K, V)], RDD[(K, W)]) ⇒ RDD[(K, (Seq[V], Seq[W]))]
$crossProduct()$	:	(RDD[T], RDD[U]) ⇒ RDD[(T, U)]
$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	RDD[(K, V)] ⇒ RDD[(K, W)] (Preserves partitioning)
$sort(c : \mathrm{Comparator[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]
$partitionBy(p : \mathrm{Partitioner[K]})$	:	RDD[(K, V)] ⇒ RDD[(K, V)]

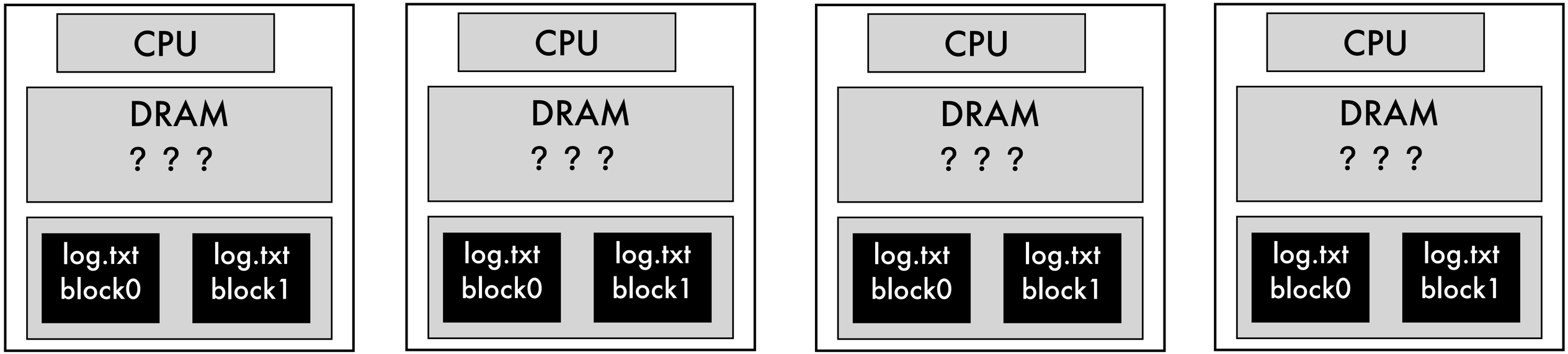
Actions: (provide data back to the "host" application)

$count()$	:	RDD[T] ⇒ Long
$collect()$	:	RDD[T] ⇒ Seq[T]
$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	RDD[T] ⇒ T
$lookup(k : \mathrm{K})$	:	RDD[(K, V)] ⇒ Seq[V] (On hash/range partitioned RDDs)
$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

How do we implement RDDs?

- In particular, how should they be stored?
  - var lines = spark.textFile("hdfs://log.txt");
  - var lower = lines.map(_.toLower());
  - var mobileViews = lower.filter(x => isMobileClient(x));
  - var howMany = mobileViews.count();

Question: should we think of RDD's like arrays?



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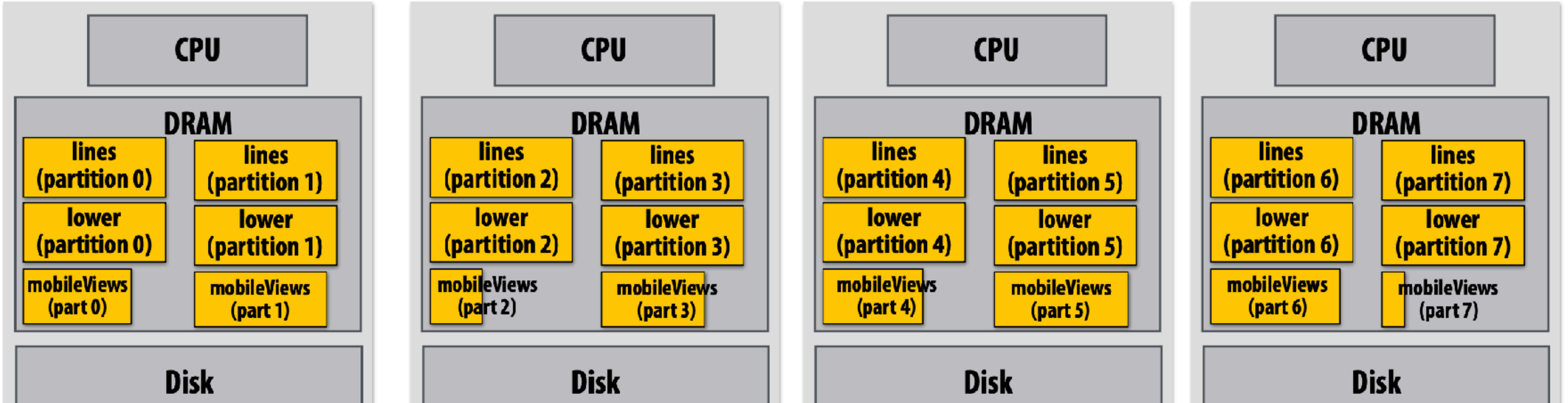
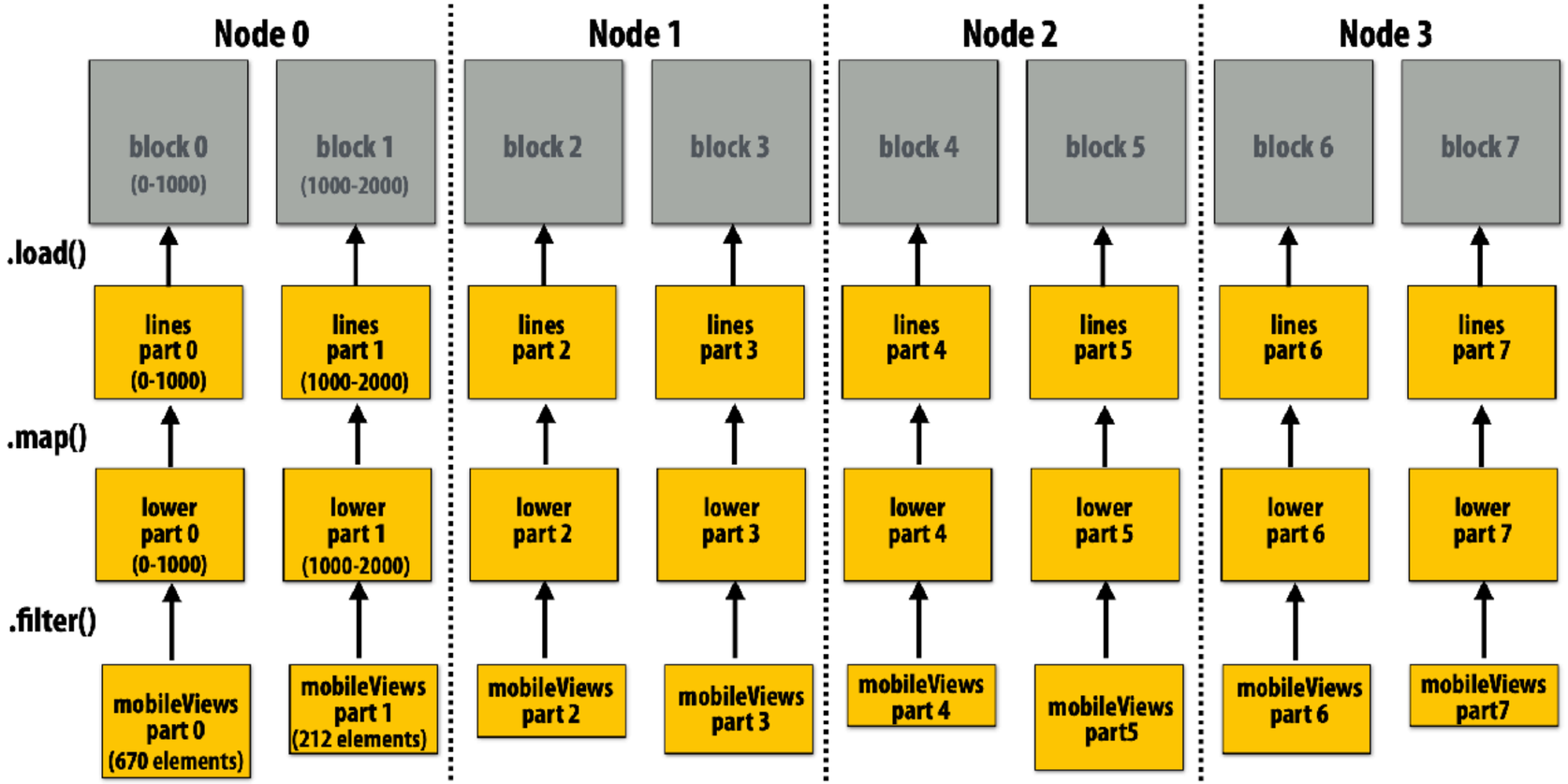
  - var mobileViews = lower.filter(x => isMobileClient(x));
  - var howMany = mobileViews.count();

Question: In-memory representation would be huge! (larger than original fle on disk)



RDD partitioning and dependencies

```
var lines = spark.textFile("hdfs://log.txt");
var lower = lines.map(_.toLower());
var mobileViews = lower.filter(x => isMobileClient(x));
var howMany = mobileViews.count();
```



Black lines show dependencies between RDD partitions.

Implementing sequence of RDD ops efficiently

```
var lines = spark.textFile("hdfs://log.txt");
var lower = lines.map(_.toLower());
var mobileViews = lower.filter(x => isMobileClient(x));
var howMany = mobileViews.count();
```

- Recall "loop fusion" from start of lecture
- The following code stores only a line of the log file in memory, and only reads input data from disk once ("streaming" solution)

```
int count = 0;
while (inputFile.eof()) {
   string line = inputFile.readLine();
   string lower = line.toLower;
   if (isMobileClient(lower))
      count++;
}
```

A simple interface for RDDs

```
var lines = spark.textFile("hdfs://log.txt");
var lower = lines.map(_.toLower());
var mobileViews = lower.filter(x => isMobileClient(x));
var howMany = mobileViews.count();
```

```
// create RDD by mapping fun onto input (parent) RDD
RDD::map(RDD parent, func) {
   return new RDDFromMap(parent, func);
}

// create RDD from text file on disk
RDD::textFile(string filename) {
   return new RDDFromTextFile(open(filename));
}

// count action (forces evaluation of RDD)
RDD::count() {
   int count = 0;
   while (hasMoreElements()) {
      var el = next();
      count++;
   }
}
```

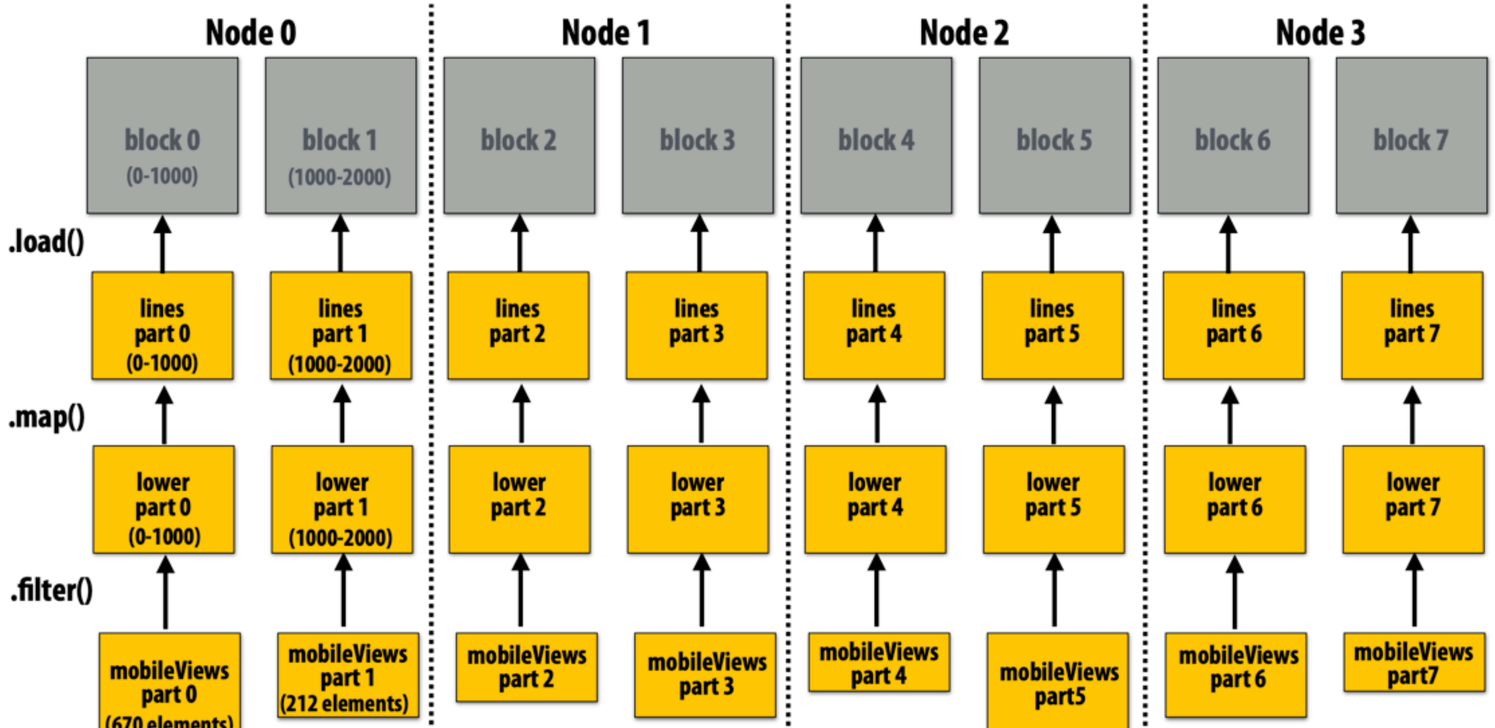
```
RDD::hasMoreElements() {
   parent.hasMoreElements();
}

// overloaded since no parent exists
RDDFromTextFile::hasMoreElements() {
   return !inputFile.eof();
}

RDDFromTextFile::next() {
   return inputFile.readLine();
}

RDDFromMap::next() {
   var el = parent.next();
   return el.toLower();
}

RDDFromFilter::next() {
  while (parent.hasMoreElements()) {
    var el = parent.next();
    if (isMobileClient(el))
      return el;
}
```

Narrow dependencies

```
var lines = spark.textFile("hdfs://log.txt");
var lower = lines.map(_.toLower());
var mobileViews = lower.filter(x => isMobileClient(x));
var howMany = mobileViews.count();
```

"Narrow dependencies" = each partition of parent RDD referenced by at most one child RDD partition

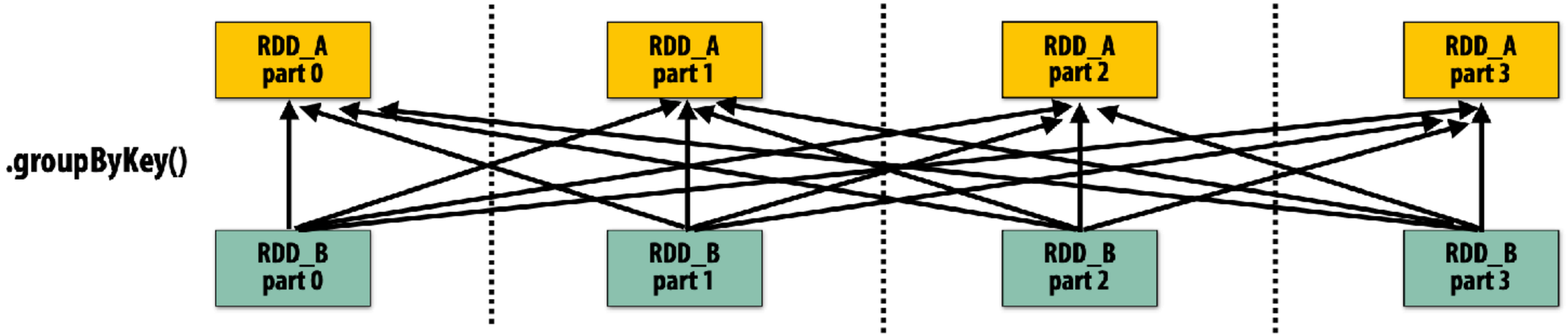
- Allows for fusing of operations
  (here: can apply map and then filter all at once on input element)
- In this example: no communication between nodes of cluster
  (communication of one int at end to perform count() reduction)



Wide dependencies

groupByKey: RDD[(K,V)] → RDD[(K,Seq[V])]

"Make a new RDD where each element is a sequence containing all values from the parent RDD with the same key."



Wide dependencies = each partition of parent RDD referenced by multiple child RDD partitions

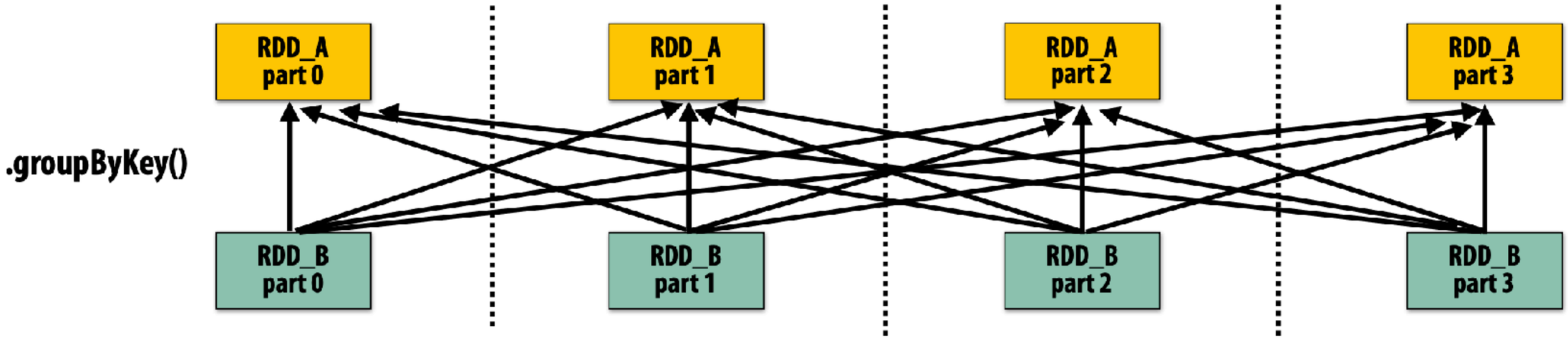
Challenges: - Must compute all of RDD_A before computing RDD_B - Example: groupByKey() may induce all-to-all communication as shown above - May trigger signifcant recompilation of ancestor lineage upon node failure (will address resilience in a few slides)

Wide dependencies

Wide dependencies = each partition of parent RDD referenced by multiple child RDD partitions

Challenges:

- Must compute all of RDD_A before computing RDD_B
  - Example: groupByKey() may induce all-to-all communication as shown above
- May trigger significant recompilation of ancestor lineage upon node failure (will address resilience in a few slides)

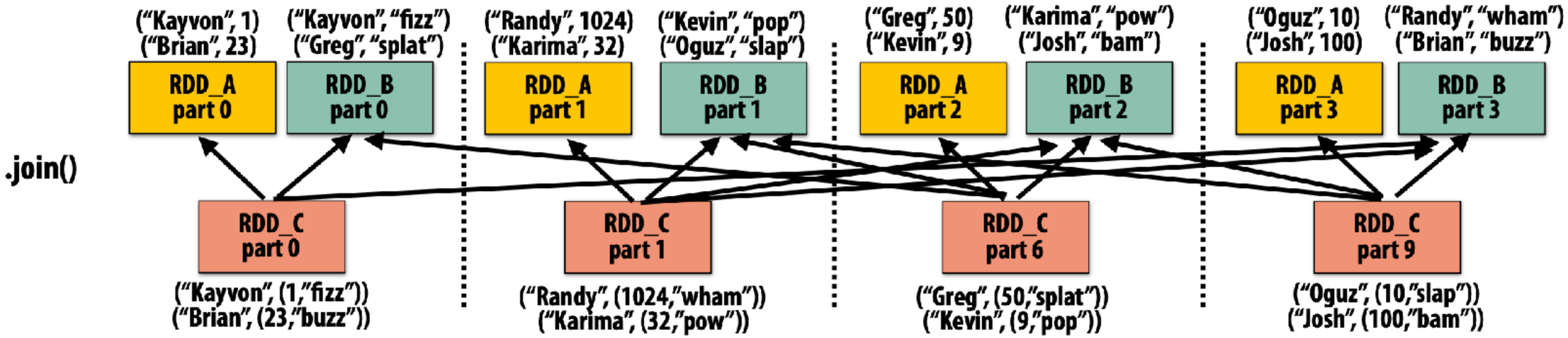


Cost of operations depends on partitioning

join: RDD[(K,V)], RDD[(K,W)] →RDD[(K,(V,W))]

Assume data in RDD_A and RDD_B are partitioned by key: hash username to partition id

RDD_A and RDD_B have **different** hash partitions: join creates **wide** dependencies



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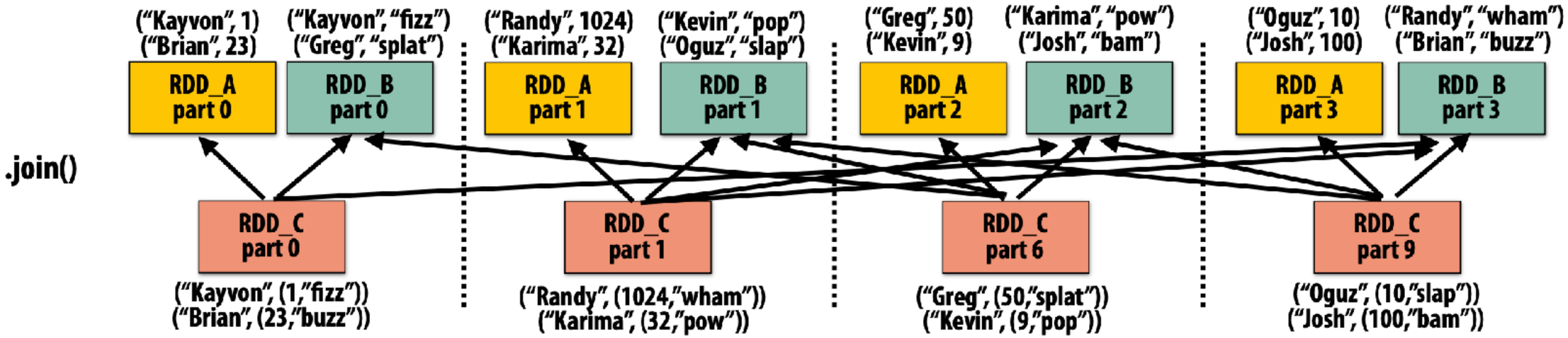
join: RDD[(K,V)], RDD[(K,W)] →RDD[(K,(V,W))]

Assume data in RDD_A and RDD_B are partitioned by key: hash username to partition id

RDD_A and RDD_B have **same** hash partition: join only creates **narrow** dependencies



PartitionBy() transformation

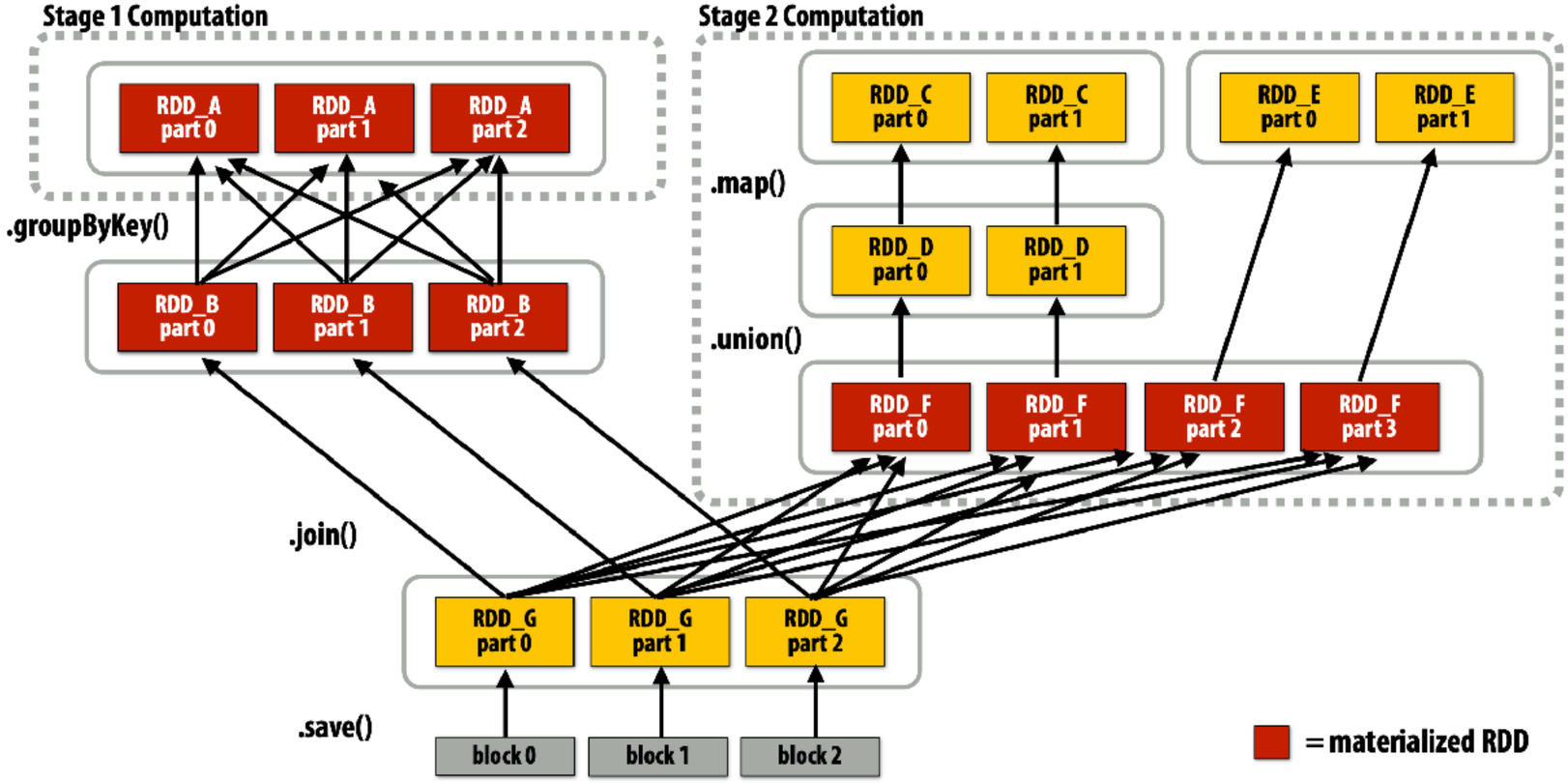
- Inform Spark on how to partition an RDD
  - e.g., HashPartitioner, RangePartitioner

```
// create RDD from file system data
var lines = spark.textFile("hdfs://log.txt");
var clientInfo = spark.textFile("hdfs://clientssupported.txt"); // (useragent, "yes"/"no")

// create RDD using filter() transformation on lines
var mobileViews = lines.filter(x => isMobileClient(x)).map(x => parseUserAgent(x));

// HashPartitioner maps keys to integers
var partitioner = spark.HashPartitioner(100);

// inform Spark of partition
// .persist() also instructs Spark to try to keep dataset in memory
var mobileViewPartitioned = mobileViews.partitionBy(partitioner) .persist();
var clientInfoPartitioned = clientInfo.partitionBy(partitioner) .persist();

// join agents with whether they are supported or not supported
// Note: this join only creates narrow dependencies
void joined = mobileViewPartitioned.join(clientInfoPartitioned);
```

.persist():

- Inform Spark this RDD materialized contents should be retained in memory
- - .persist(RELIABLE) = store contents in durable storage (like a checkpoint)

Scheduling Spark computations

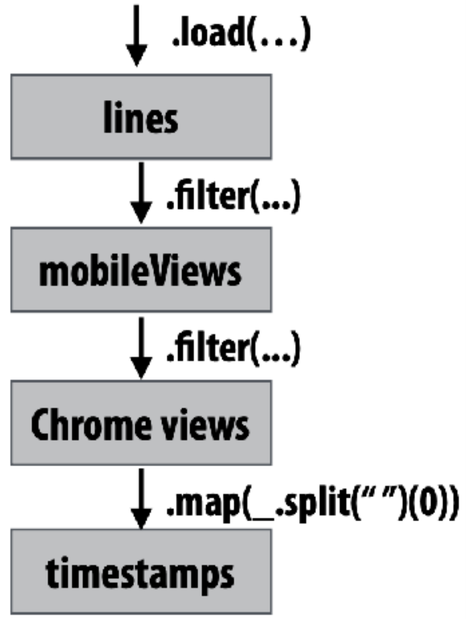


- Actions (e.g., save()) trigger evaluation of Spark lineage graph.
  - Stage 1 Computation: do nothing since input already materialized in memory
  - Stage 2 Computation: evaluate map in fused manner, only actually materialize RDD F
  - Stage 3 Computation: execute join (could stream the operation to disk, do not need to materialize)

Implementing resilience via lineage

- RDD transformations are bulk, deterministic, and functional
  - Implication: runtime can always reconstruct contents of RDD from its lineage (the sequence of transformations used to create it)
  - Lineage is a log of transformations
  - Efficient: since log records bulk data-parallel operations, overhead of logging is low (compared to logging fine-grained operations, like in a database)

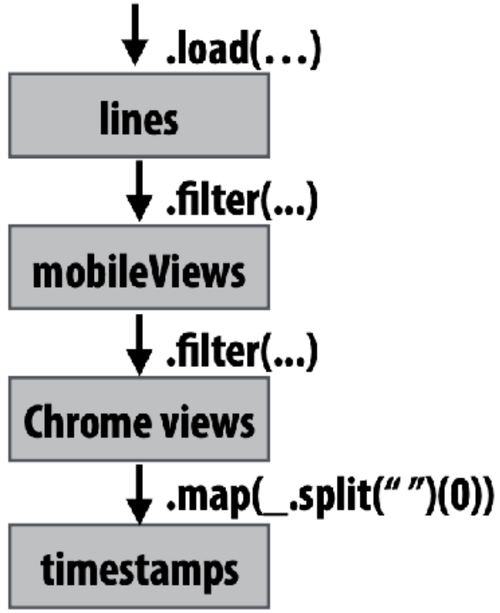
```
// create RDD from file system data
var lines = spark.textFile("hdfs://15418log.txt");
// create RDD using filter() transformation on lines
var mobileViews = lines.filter((x: String) => isMobileClient(x));
// 1. create new RDD by filtering only Chrome views
// 2. for each element, split string and take timestamp of // page view (first element)
// 3. convert RDD To a scalar sequence (collect() action)
var timestamps = mobileView.filter(_.contains("Chrome")) .map(_.split(" ")(0));
```

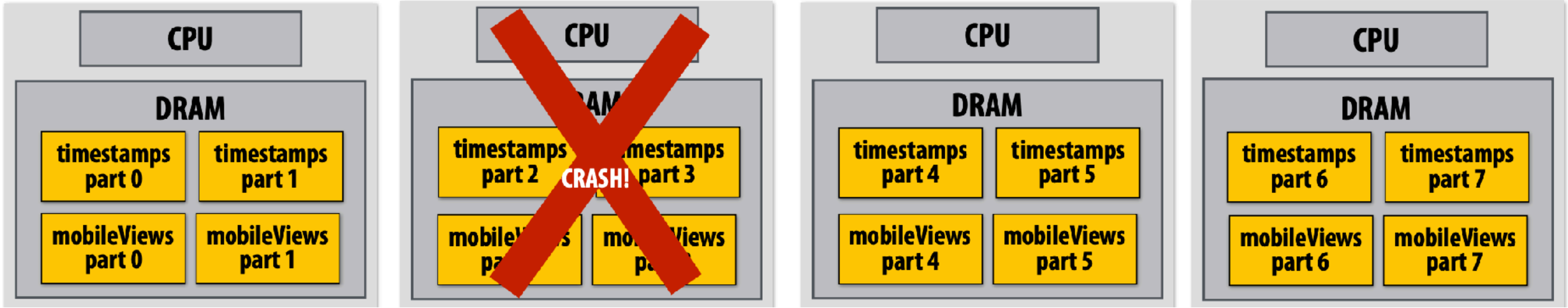


Upon node failure: recompute lost RDD partitions from lineage

Must reload required subset of data from disk and recompute entire sequence of operations given by lineage to regenerate partitions 2 and 3 of RDD timestamps.

Note: (not shown): file system data is replicated so assume blocks 2 and 3 remain accessible to all nodes





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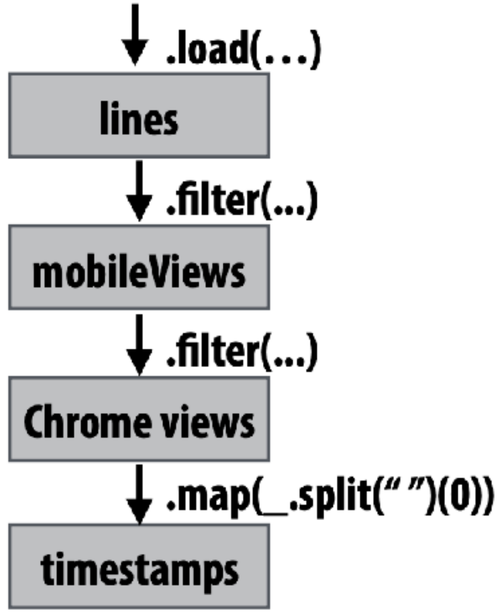
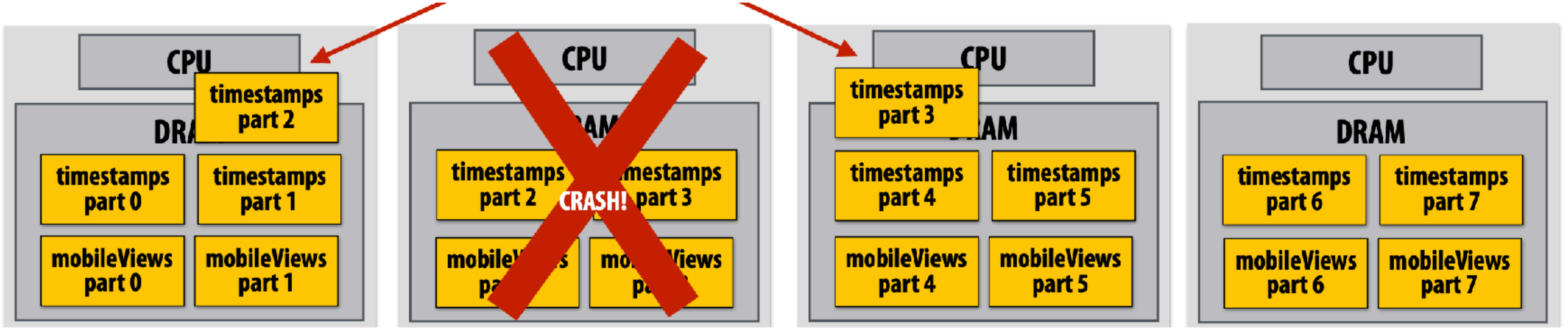
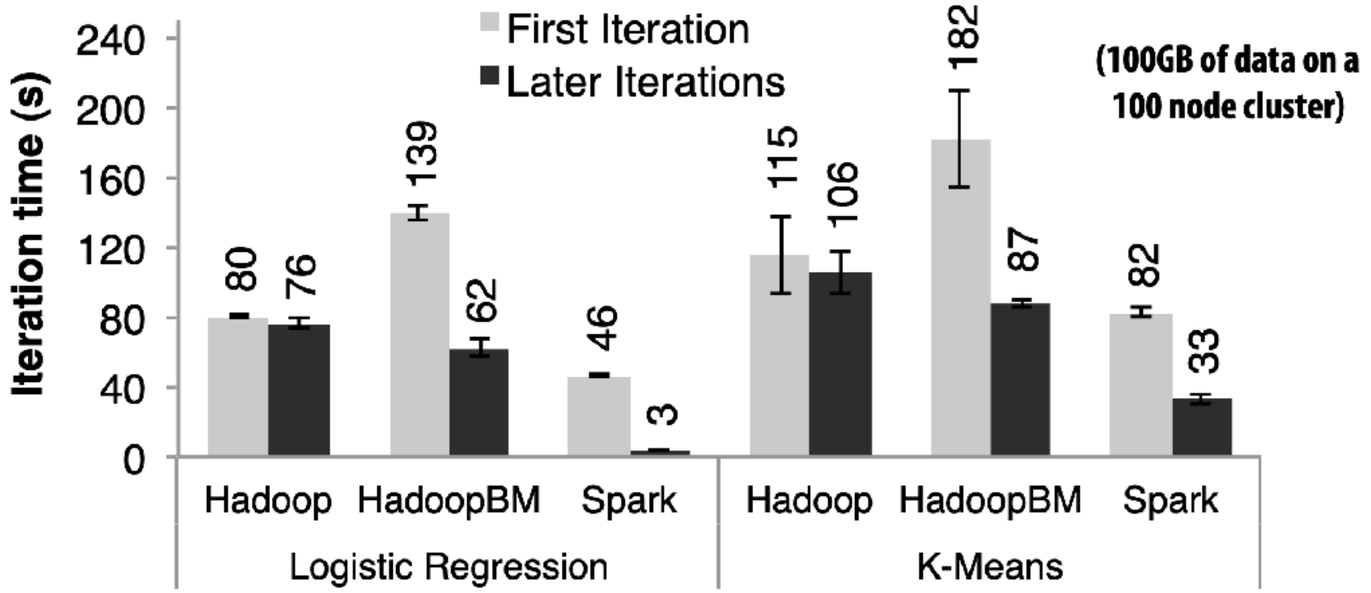




Spark Performance



HadoopBM = Hadoop Binary In-Memory (convert text input to binary, store in in-memory version of HDFS)

- the baseline parses text input in each iteration of an iterative algorithm

HadoopBM's frst iteration is slow because it runs an extra Hadoop job to copy binary form of input data to in memory HDFS

Accessing data from HDFS, even if in memory has high overhead:

- Multiple mem copies in fle system + a checksum
- Conversion from serialized form to Java object

Caution: "scale out" is not the entire story

- Distributed systems designed for cloud execution address many difficult challenges, and have been instrumental in the explosion of "big-data" computing and large-scale analytics
  - Scale-out parallelism to many machines
  - Resiliency in the face of failures
  - Complexity of managing clusters of machines
- But scale out is not the whole story:

20 Iterations of Page Rank

scalable system	cores	twitter	uk-2007-05
GraphChi [10]	2	3160s	6972s
Stratosphere [6]	16	2250s	-
X-Stream [17]	16	1488s	-
Spark [8]	128	857s	1759s
Giraph [8]	128	596s	1235s
GraphLab [8]	128	249s	833s
GraphX [8]	128	419s	462s
Single thread (SSD)	1	300s	651s
Single thread (RAM)	1	275s	-

name	twitter_rv [11]	uk-2007-05 [4]
nodes	41,652,230	105,896,555
edges	1,468,365,182	3,738,733,648
size	5.76GB	14.72GB

Vertex order (SSD)	1	300s	651s
Vertex order (RAM)	1	275s	-
Hilbert order (SSD)	1	242s	256s
Hilbert order (RAM)	1	110s	-

Further optimization of the baseline brought time down to 110s

["Scalability! At what COST?" McSherry et al. HotOS 20

Caution: "scale out" is not the entire story

Label Propagation
[McSherry et al. HotOS 2015]

scalable system	cores	twitter	uk-2007-05
Stratosphere [6]	16	950s	-
X-Stream [17]	16	1159s	-
Spark [8]	128	1784s	$\geq$ 8000s
Giraph [8]	128	200s	$\geq$ 8000s
GraphLab [8]	128	242s	714s
GraphX [8]	128	251s	800s
Single thread (SSD)	1	153s	417s

from McSherry 2015:

"The published work on big data systems has fetishized scalability as the most important feature of a distributed data processing platform. While nearly all such publications detail their system's impressive scalability, few directly evaluate their absolute performance against reasonable benchmarks. To what degree are these systems truly improving performance, as opposed to parallelizing overheads that they themselves introduce?"

COST: "Configuration that Outperforms a Single Thread"

Perhaps surprisingly, many published systems have unbounded COST—i.e., no configuration outperforms the best single-threaded implementation—for all of the problems to which they have been applied.

BID Data Suite (1 GPU accelerated node)
[Canny and Zhao, KDD 13]

Page Rank

System	Graph VxE	Time(s)	Gflops	Procs
Hadoop	?x1.1B	198	0.015	50x8
Spark	40Mx1.5B	97.4	0.03	50x2
Twister	50Mx1.4B	36	0.09	60x4
PowerGraph	40Mx1.4B	3.6	0.8	64x8
BIDMat	60Mx1.4B	6	0.5	1x8
BIDMat+disk	60Mx1.4B	24	0.16	1x8

Latency Dirichlet Allocation (LDA)

System	Docs/hr	Gflops	Procs
Smola[15]	1.6M	0.5	100x8
PowerGraph	1.1M	0.3	64x16
BIDMach	3.6M	30	1x8x1

Performance improvements to Spark

- With increasing DRAM sizes and faster persistent storage (SSD), there is interest in improving the CPU utilization of Spark applications
  - Goal: reduce “COST”

- Efforts looking at efficient code generation to Spark ecosystem (e.g., generate SIMD kernels, target accelerators like GPUs, etc.) to close the gap on single node performance
  - - See Spark’s Project Tungsten

- High-performance computing ideas are infuencing design of future performance oriented distributed systems
  - Conversely: the scientifc computing community has a lot to learn from the distributed computing community about elasticity and utility computing

Spark summary

- Introduces opaque sequence abstraction (RDD) to encapsulate intermediates of cluster computations (previously… frameworks like Hadoop/MapReduce stored intermediates in the fle system)
  - Observation: “files are a poor abstraction for intermediate variables in largescale data-parallel programs”
  - RDDs are read-only, and created by deterministic data-parallel operators
  - Lineage tracked and used for locality-aware scheduling and fault-tolerance (allows recomputation of partitions of RDD on failure, rather than restore from checkpoint *)
    - Bulk operations allow overhead of lineage tracking (logging) to be low.

- Simple, versatile abstraction upon which many domain-specifc distributed computing frameworks are being implemented.
  - See Apache Spark project: spark.apache.org

* Note that .persist(RELIABLE) allows programmer to request checkpointing in long lineage situations.

Modern Spark ecosystem

Compelling feature: enables integration/composition of multiple domain-specific frameworks (since all collections implemented under the hood with RDDs and scheduled using Spark scheduler)


```
sqlCtx = new HiveContext(sc)
results = sqlCtx.sql(
  "SELECT * FROM people")
names = results.map(lambda p: p.name)
```

Interleave computation and database query
Can apply transformations to RDDs produced by SQL queries

Machine learning library build on top of Spark abstractions.

```
points = spark.textFile("hdfs://...")
              .map(parsePoint)

model = KMeans.train(points, k=10)
```

GraphLab-like library built on top of Spark abstractions.

```
graph = Graph(vertices, edges)
messages = spark.textFile("hdfs://...")
graph2 = graph.joinVertices(messages) {
  (id, vertex, msg) => ...
}
```