

# Parallelism

CS 242

November 8, 2017

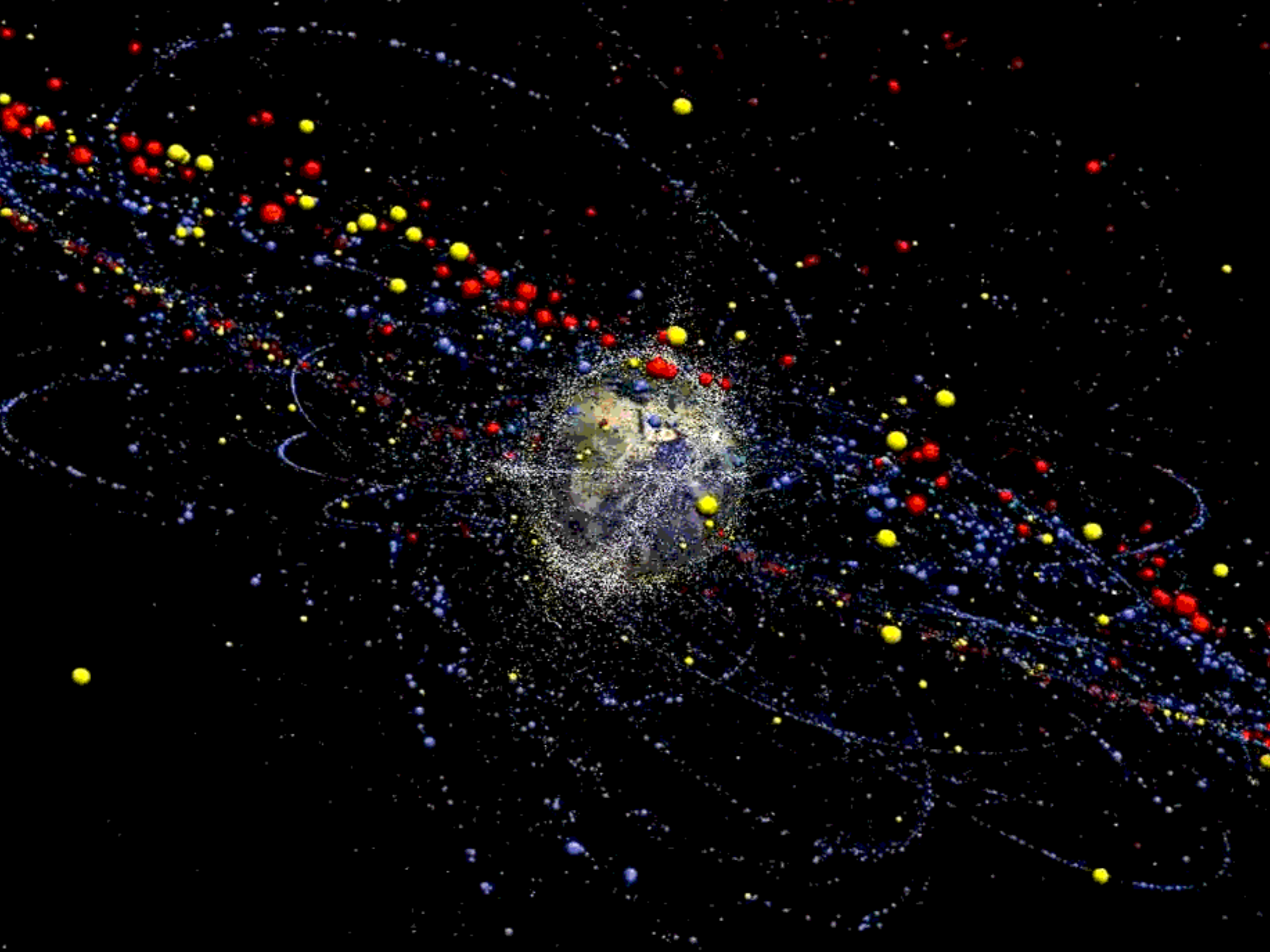
# Today's goals

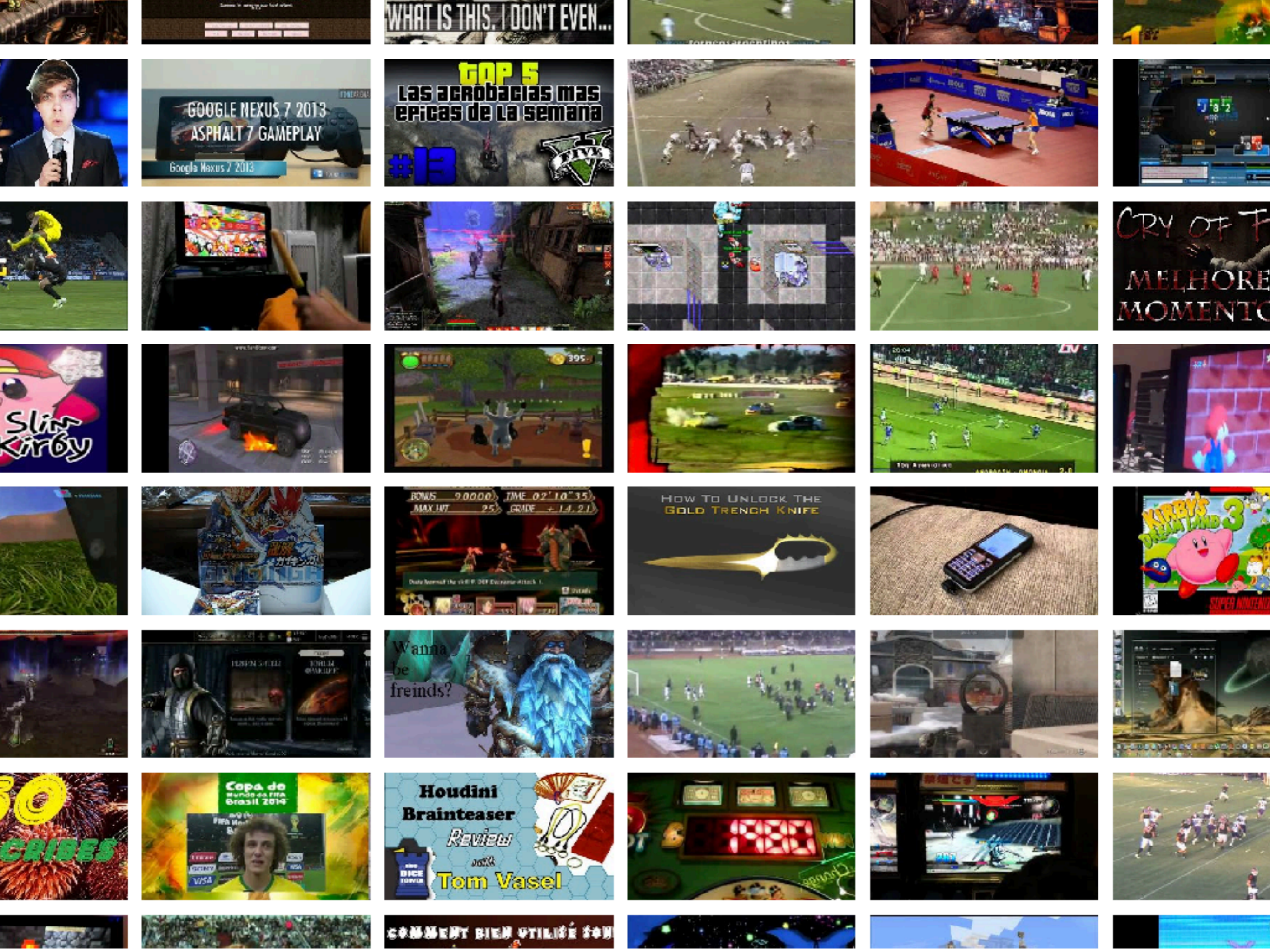
- **Basic approach to parallel programming**
- **Survey of parallel programming models**
- **Tradeoffs in representations**

# Parallelism:

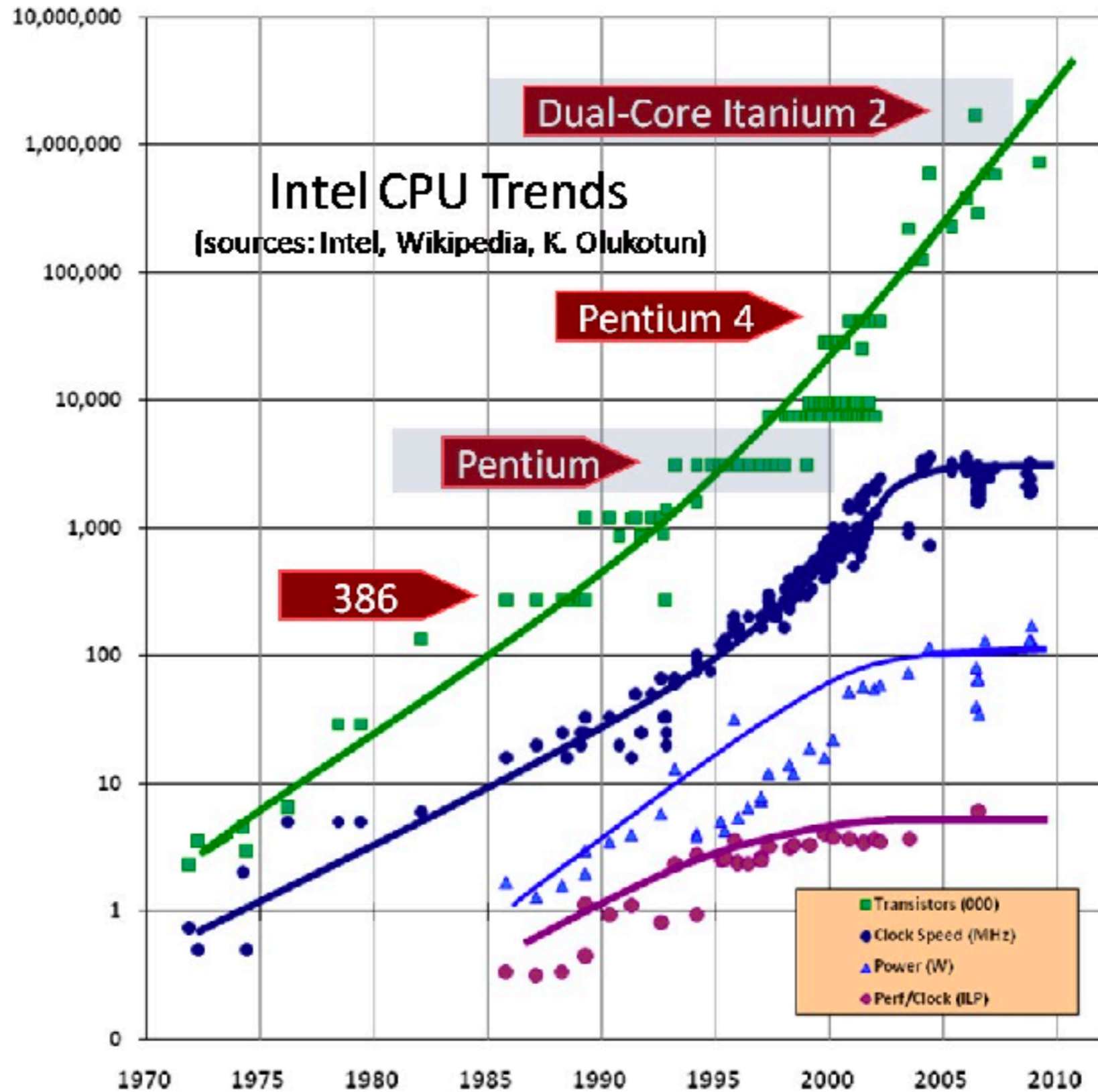
**Use multiple resources to accomplish a goal faster.**







# Single-core is tapped out (mostly)



# Creating a parallel program



**Decomposition**

Subproblems  
(a.k.a. "tasks",  
"work to do")



**Assignment**

Parallel Threads \*\*  
("workers")

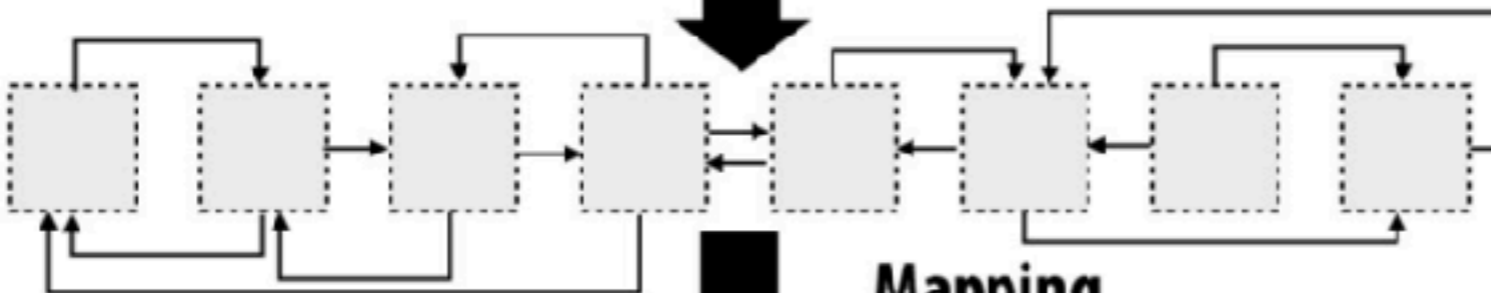


\*\* I had to pick a term



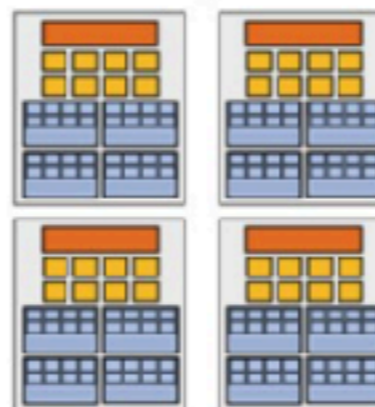
**Orchestration**

Parallel program  
(communicating  
threads)



**Mapping**

Execution on  
parallel machine



**These responsibilities may be assumed by  
the programmer, by the system (compiler,  
runtime, hardware), or by both!**



# Sum all elements of a vector

```
fn main() {  
    let vec: Vec<i64> = (0..100000).collect();  
  
    let mut sum = 0;  
    for i in vec {  
        sum += i;  
    }  
  
    println!("Sum: {}", sum);  
}
```

# 1. Decomposition: reduction

```
use std::thread;
use std::sync::Arc;

const NUM_WORKERS: usize = 8;
```

```
fn main() {
    let vec: Arc<Vec<i64>> = Arc::new((0..100000).collect());

    let chunk_size = vec.len() / NUM_WORKERS;

    let handles: Vec<thread::JoinHandle<i64>> =
        (0..NUM_WORKERS).into_iter().map(|i| {
            let vec_ref = vec.clone();
            thread::spawn(move || {
                let mut sum = 0;
                for j in (i * chunk_size)..((i + 1) * chunk_size) {
                    sum += vec_ref[j];
                }
                sum
            })
        });
```

4. Mapping

2. Assignment

```
    let mut final_sum = 0;
    for handle in handles {
        final_sum += handle.join().unwrap();
    }
```

3. Orchestration

```
    println!("Sum: {}", final_sum);
```

```
}
```

# OpenMP parallelizes for loops on CPU

```
int main() {  
    int x[] = {1, 2, 3, 4, 5};  
  
    #pragma omp parallel for  
    for (int i = 0; i < 5; ++i) {  
        x[i] = x[i] + 1;  
    }  
}
```

**“Each iteration of this loop is independent”**

# CUDA parallelizes functions on the GPU

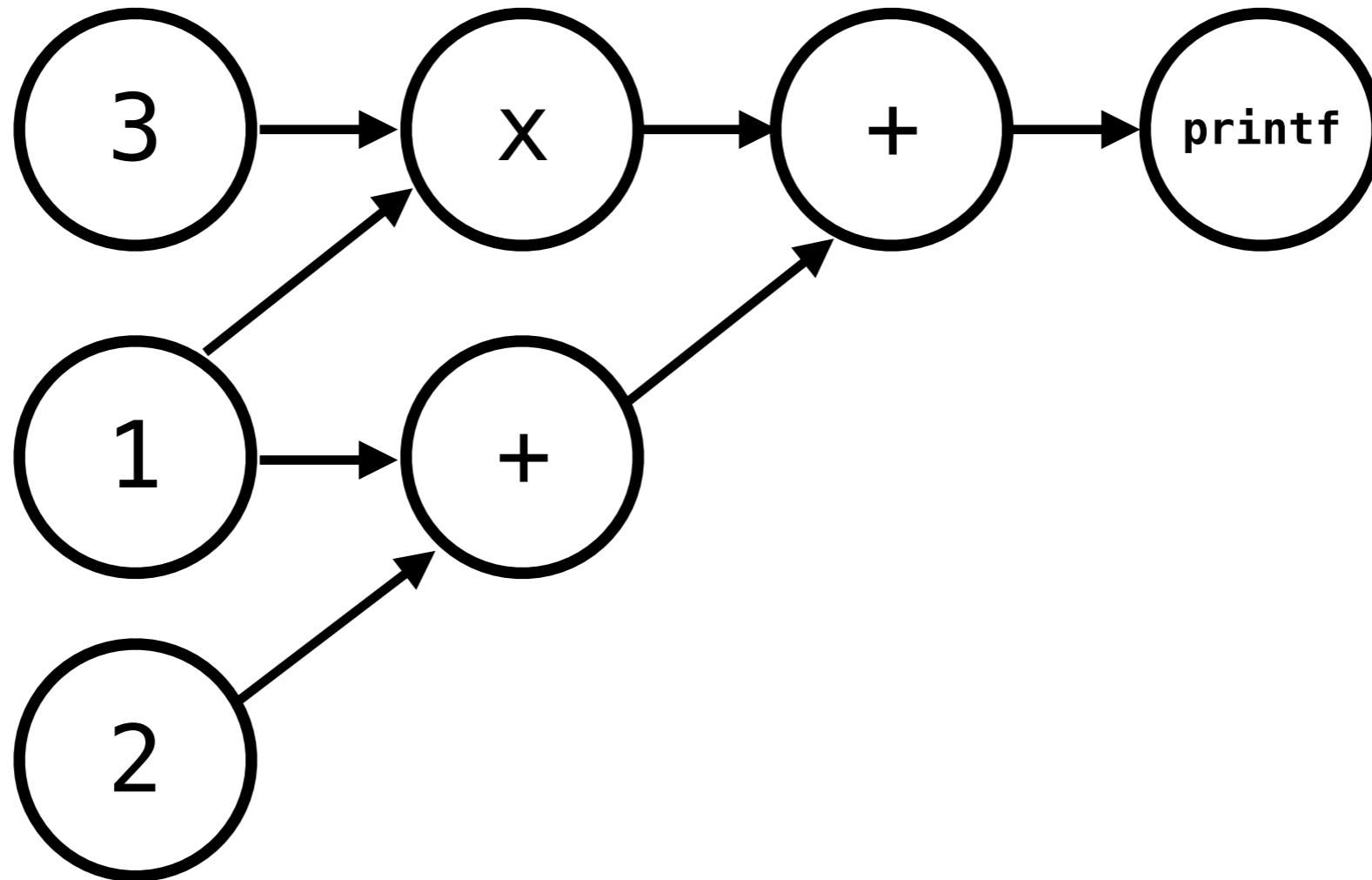
```
__global__ void add_one(int *x) {  
    int index = blockIdx.x * blockDim.x + threadIdx.x;  
    x[index] = x[index] + 1;  
}
```

```
int main() {  
    int x[256];  
    int* x_gpu;  
    cudaMalloc(&x_gpu, 256 * sizeof(int));  
    cudaMemcpy(x_gpu, x, 256 * sizeof(int),  
              cudaMemcpyHostToDevice);  
  
    add_one<<<1, 256>>>(x_gpu);  
}
```

**“Each call this function is independent”**

**Problem: most of the hard work is left  
to the programmer.**

```
int x = 1;  
int y = x + 2;  
int z = x * 3;  
printf("%d\n", z + y)
```



# TensorFlow = dataflow + tensors

```
import tensorflow as tf

a = tf.placeholder(tf.float32)
b = tf.placeholder(tf.float32)

c = a + b
d = a * c

with tf.Session() as sess:
    result = sess.run([d], {a: 2, b: 3})
    print(result)
```

# TensorFlow = dataflow + tensors

```
import tensorflow as tf

x = tf.constant([[1.0, 2.0],
                 [3.0, 4.0]])
y = tf.constant([[1.0, 0.0],
                 [0.0, 1.0]])
z = tf.matmul(x, y)

with tf.Session() as sess:
    print(sess.run(z))
```



# Spark = RDDFlow (RDD[T] = Vec<T>)

## 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

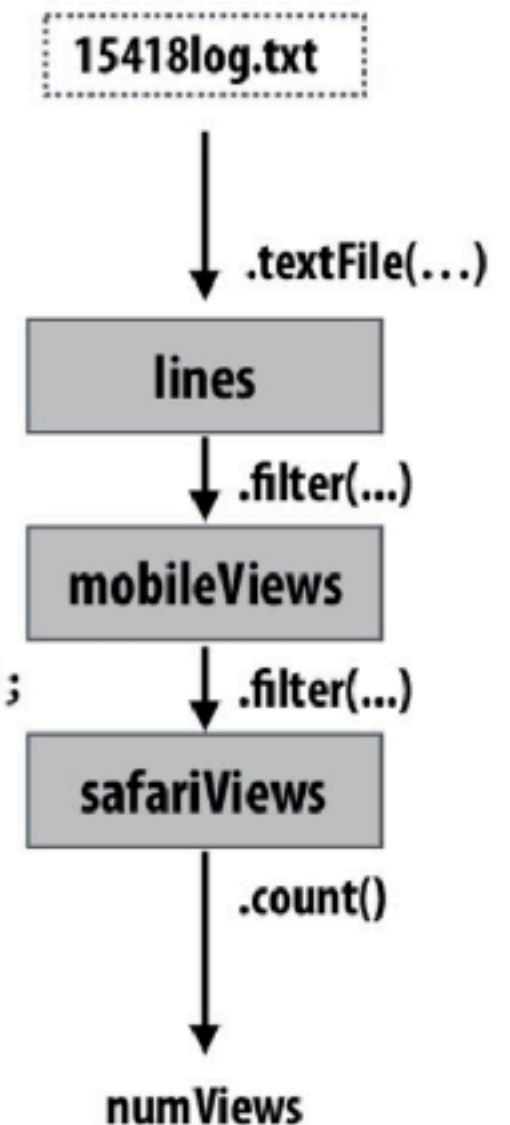
```
// create RDD from file system data
var lines = spark.textFile("hdfs://15418log.txt");

// 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



# Spark supports DAGs

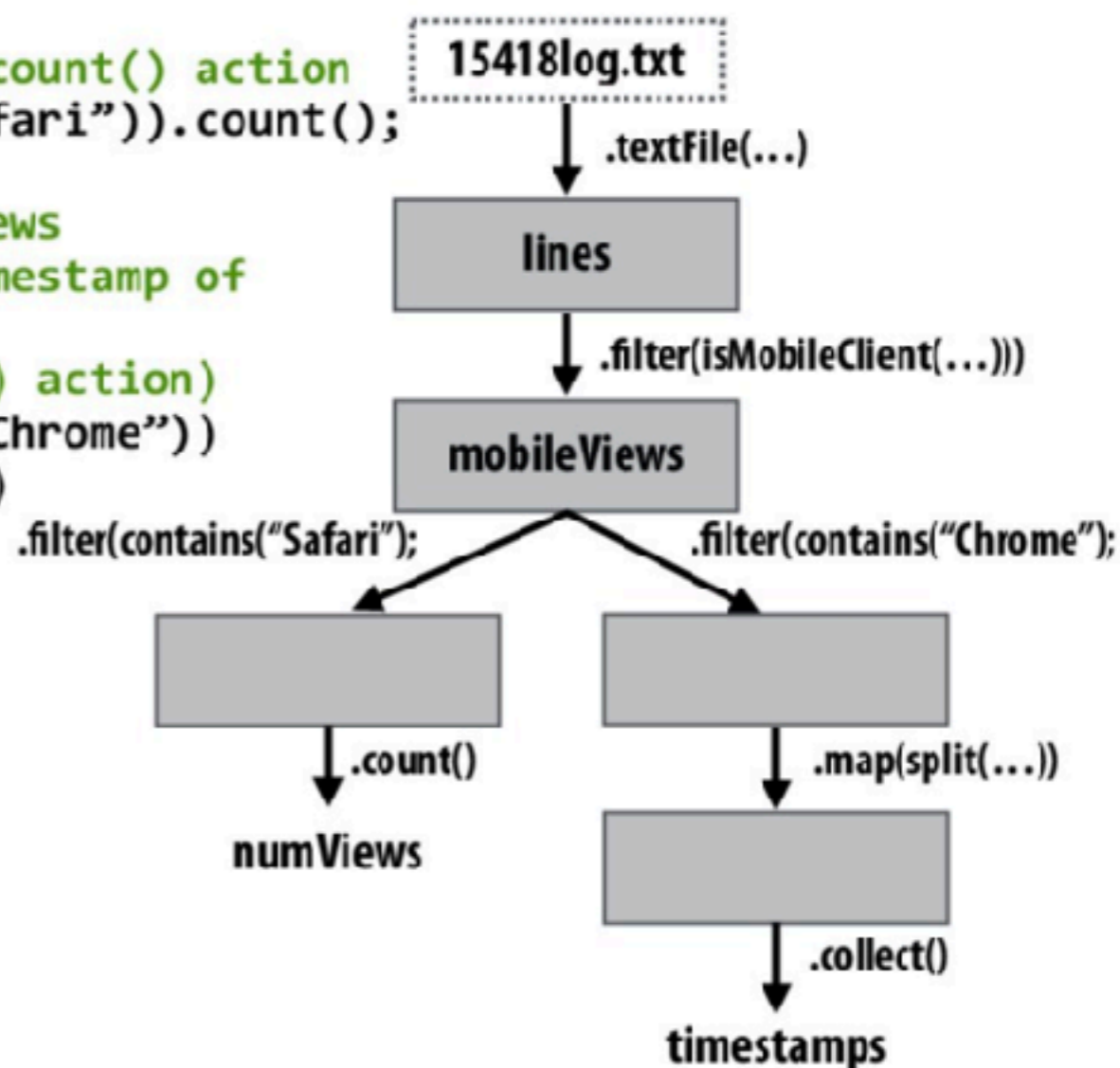
```
// create RDD from file system data
var lines = spark.textFile("hdfs://15418log.txt");

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

// 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();
```



# Spark transformations and actions

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

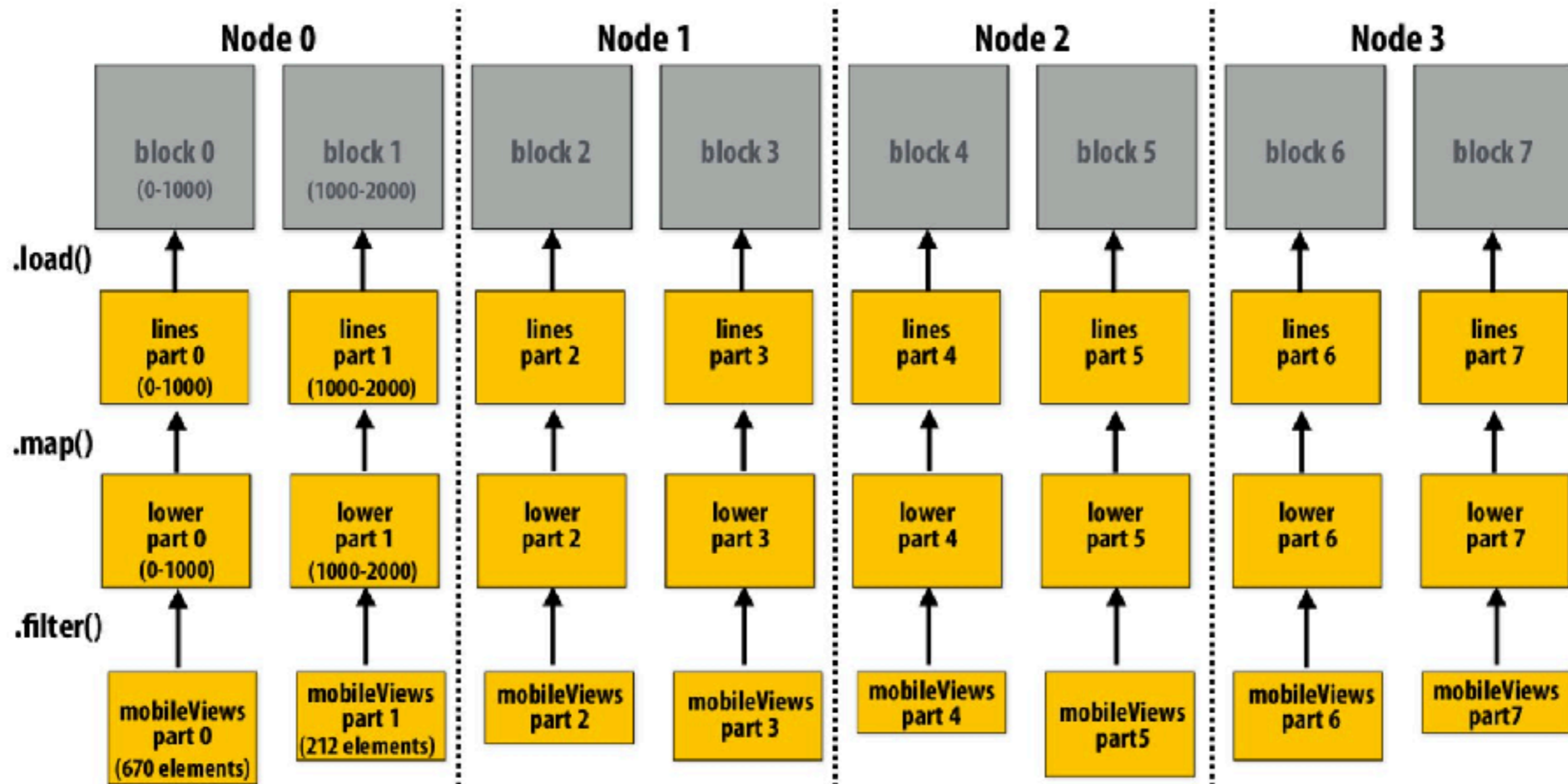
<i>map</i> ( $f : T \Rightarrow U$ )	:	$\text{RDD}[T] \Rightarrow \text{RDD}[U]$
<i>filter</i> ( $f : T \Rightarrow \text{Bool}$ )	:	$\text{RDD}[T] \Rightarrow \text{RDD}[T]$
<i>flatMap</i> ( $f : T \Rightarrow \text{Seq}[U]$ )	:	$\text{RDD}[T] \Rightarrow \text{RDD}[U]$
<i>sample</i> ( <i>fraction</i>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

**Actions: (provide data back to the “host” application)**

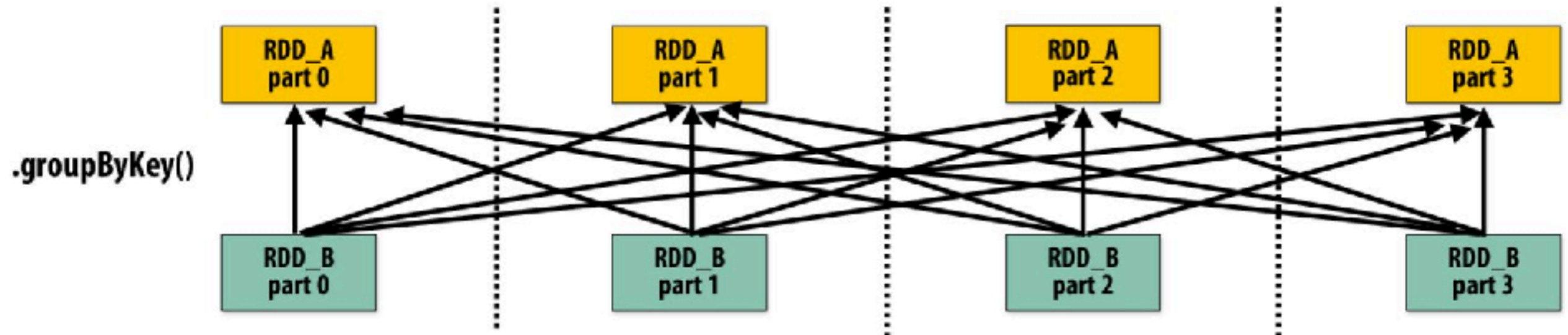
<i>count</i> ()	:	$\text{RDD}[T] \Rightarrow \text{Long}$
<i>collect</i> ()	:	$\text{RDD}[T] \Rightarrow \text{Seq}[T]$
<i>reduce</i> ( $f : (T, T) \Rightarrow T$ )	:	$\text{RDD}[T] \Rightarrow T$
<i>lookup</i> ( $k : K$ )	:	$\text{RDD}[(K, V)] \Rightarrow \text{Seq}[V]$ (On hash/range partitioned RDDs)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

# Solution #1: partitioning

```
var lines = spark.textFile("hdfs://15418log.txt");  
var lower = lines.map(_.toLowerCase());  
var mobileViews = lower.filter(x => isMobileClient(x));  
var howMany = mobileViews.count();
```



# Solution #1: partitioning



# Solution #2: streaming

```
fn main() {  
    // Non-streaming  
    let v = (0..(1024i64*1024*1024*1024)).into_iter();  
    let v1: Vec<i64> = v.collect();  
    let mut v2 = Vec::new();  
    for x in v1 {  
        v2.push(x + 1);  
    }  
    println!("{}", v2[0]);  
  
    // Streaming  
    let v = (0..(1024i64*1024*1024*1024)).into_iter();  
    let mut v2 = v.map(|x| x + 1);  
    println!("{}", v2.next().unwrap());  
}
```