

# Concurrency: Multi-core Programming & Data Processing

## Data Parallelism



**Prof. P. Felber**

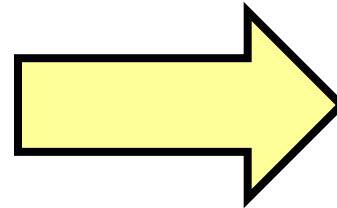
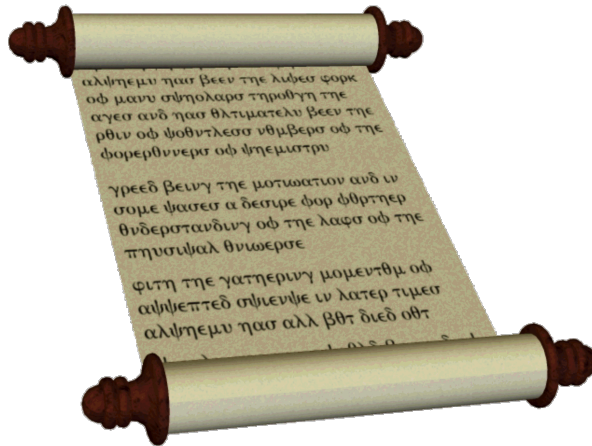
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<http://iiun.unine.ch/>

*Based on slides by Maurice Herlihy and Nir Shavit*

# “WordCount”

- Count then number of occurrences of words in a text



alpha  $\rightarrow$  8

bravo  $\rightarrow$  3

charlie  $\rightarrow$  9

● ● ●

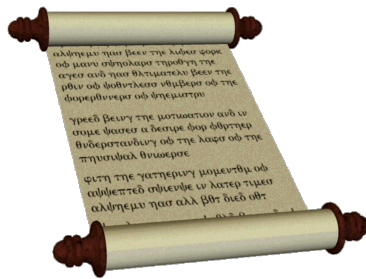
zulu  $\rightarrow$  1

# Easy to do sequentially...

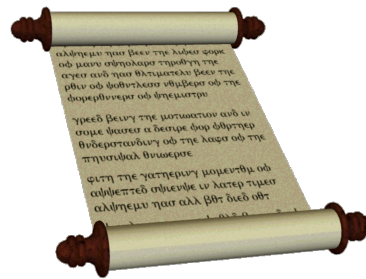
## What about in parallel?

# MapReduce

Split text among mapping threads

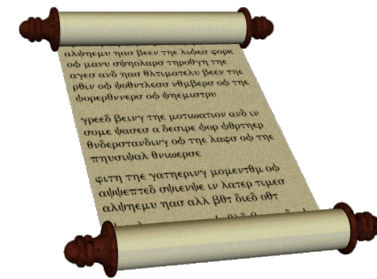


Chapter 1



Chapter 2

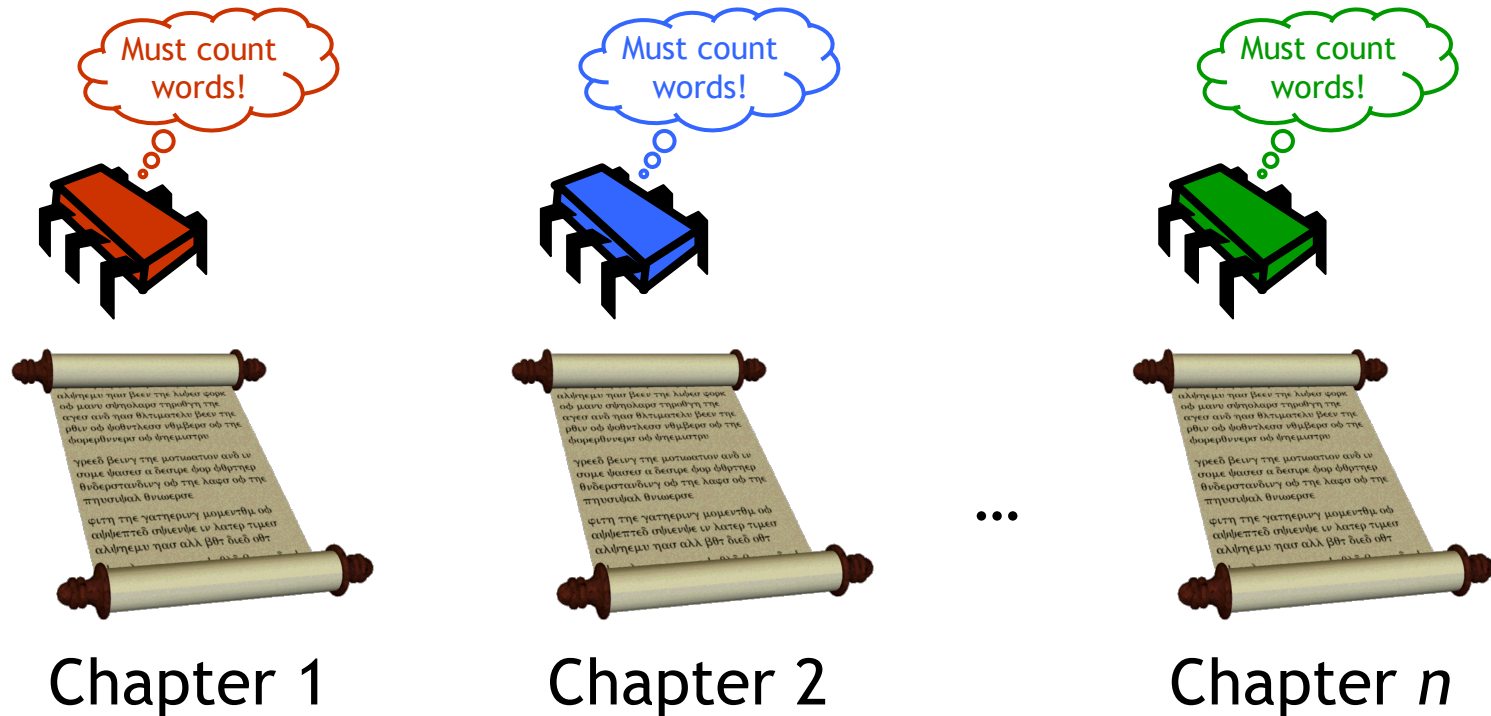
...



Chapter  $n$

# Map Phase

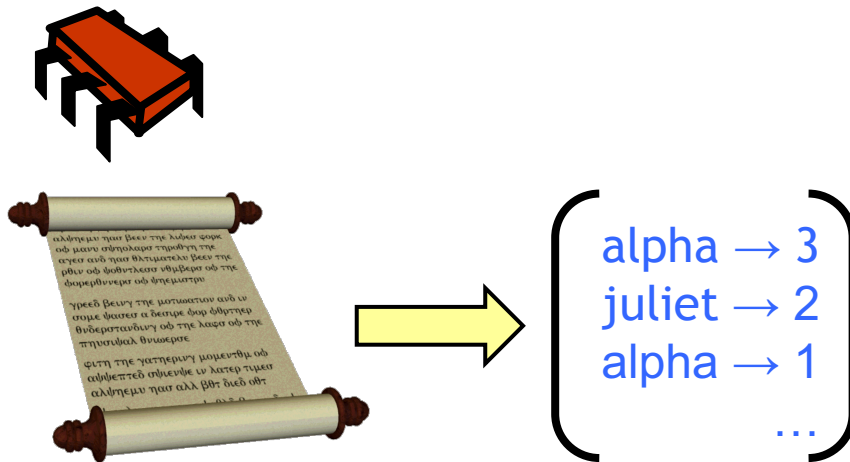
One mapping thread per chapter



# Map Phase

Each mapper produces a stream of key-value pairs

key : word  
 value : local count



Chapter 1

# Mapper Class

Input: document fragment    Key: individual word    Value: local count

```

abstract class Mapper<IN, K, V>
    extends RecursiveTask<Map<K, V>> {
    IN input;
    public void setInput(IN anInput) {
        input = anInput;
    }
}
  
```

Produces a map: word → count

A task that runs in parallel with other tasks

Initialize input: which document fragment?

# WordCount Mapper

Document fragment is list of words      Map each word... to its count in the fragment

```

class WordCountMapper extends
  mapreduce.Mapper<List<String>, String, Long> {
  Map<String, Long> compute() {
    Map<String, Long> map = new HashMap<>();
    for (String word : input) {
      map.merge(word,
                1L,
                (x, y) -> x + y);
    }
    return map;
  }
}
  
```

Construct local word count

Create map to hold output

Examine each word in the document fragment

Increment that word's count in the map

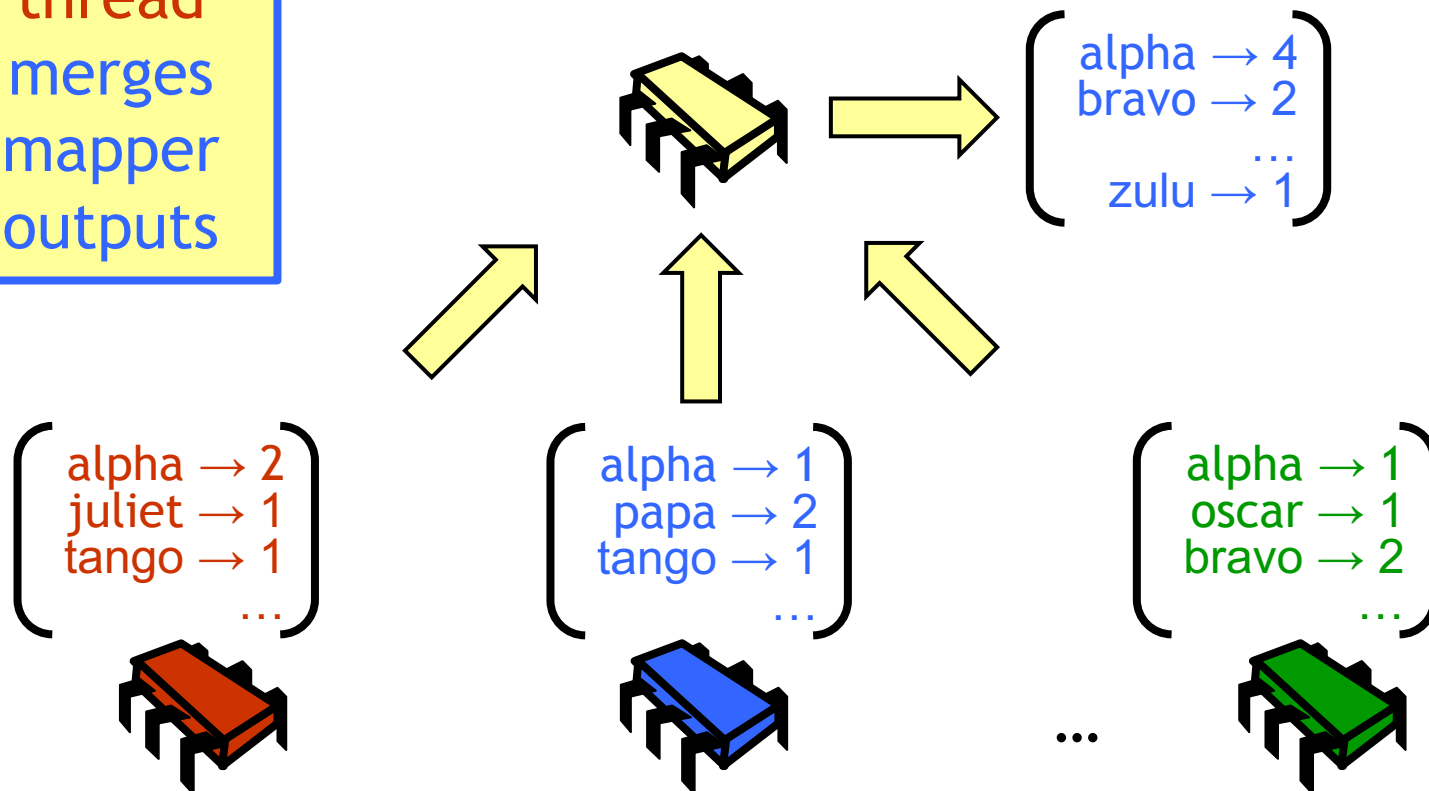
When the local count is complete, return the map

# Reduce Phase

One reducer thread merges mapper outputs

The reducer produces a stream of key-value pairs

key : word  
 value : word count





# Reducer Class

Each reducer is given a single key (word)...

```
abstract class Reducer<K, V, OUT>
    extends RecursiveTask<OUT> {
```

It produces a single  
summary value (total  
count for that word)

K key;

List<V> valueList;

...and a list of associated values (word  
count per fragment)

```
    public void setInput(K aKey,
                        List<V> aList) {
```

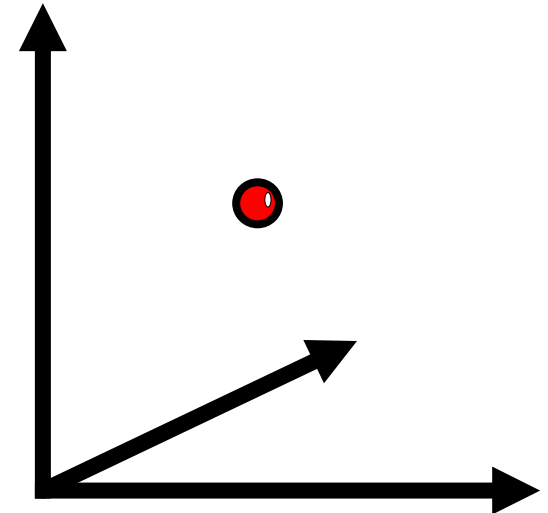
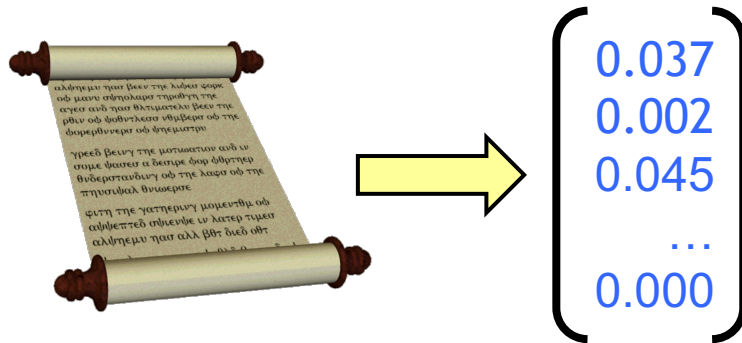
```
        key = aKey;
```

```
        valueList = aList;
```

```
    }
```

```
}
```

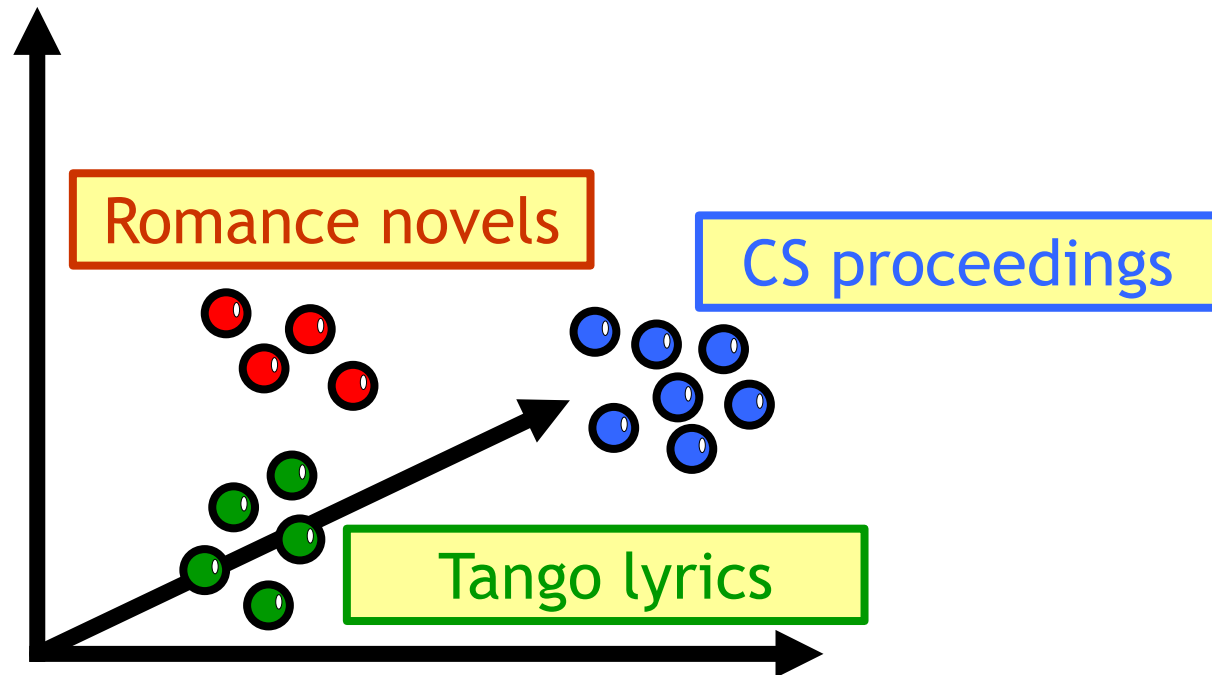
# WordCount



Normalizing document  
 word count gives a  
**fingerprint** vector

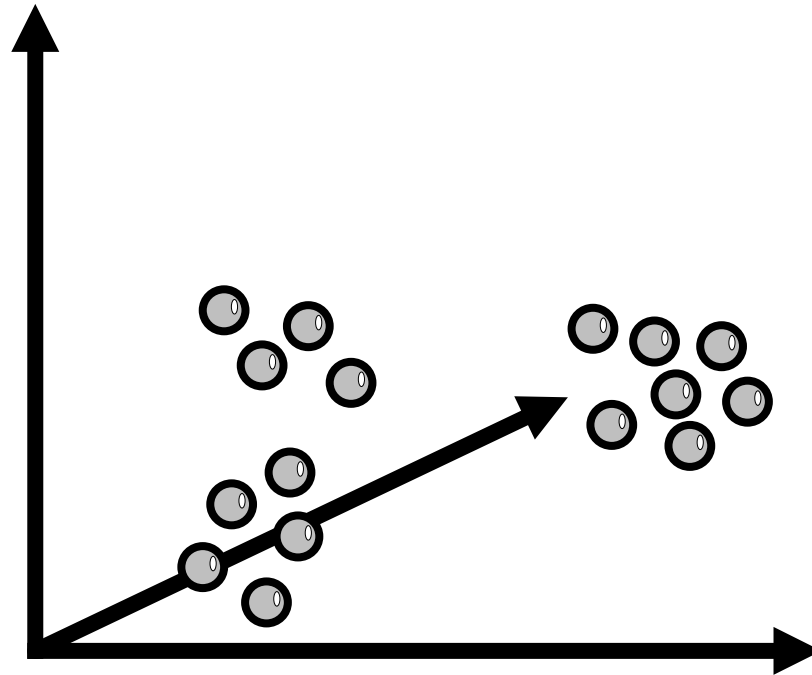
A **fingerprint** is a point  
 in a high-dimensional  
 space

# Clustering



Similar documents have their fingerprints close to each other

# K-Means

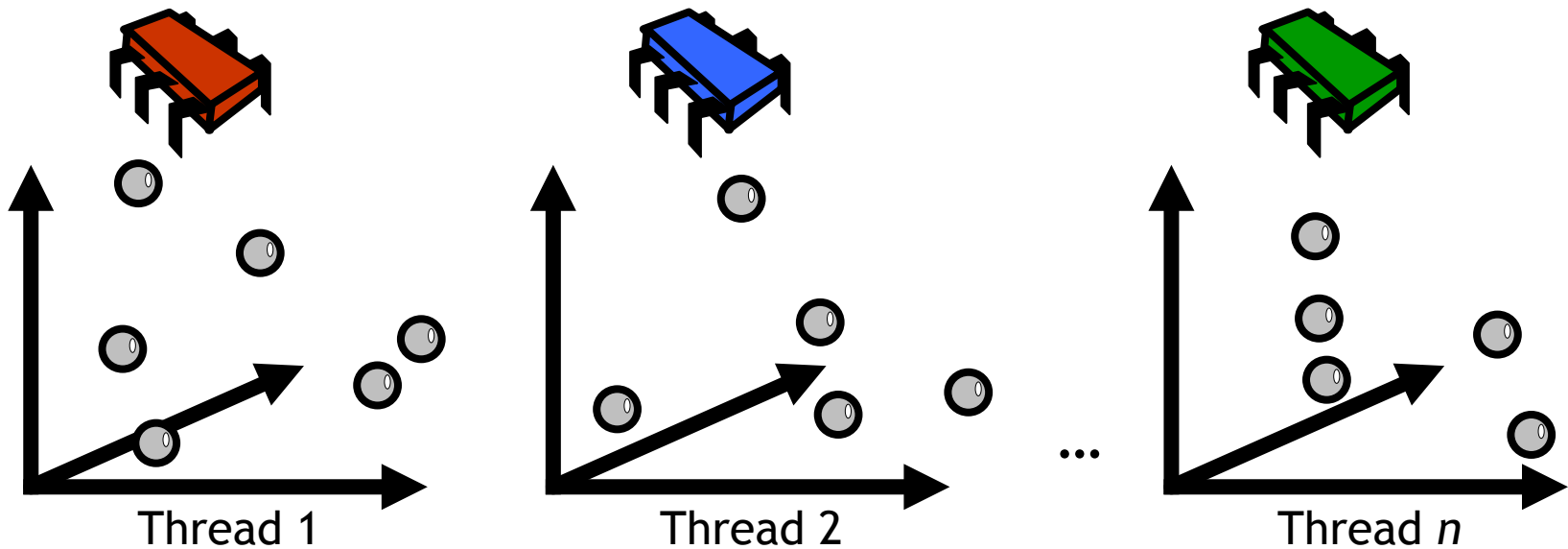


Find  $k$  clusters from raw data

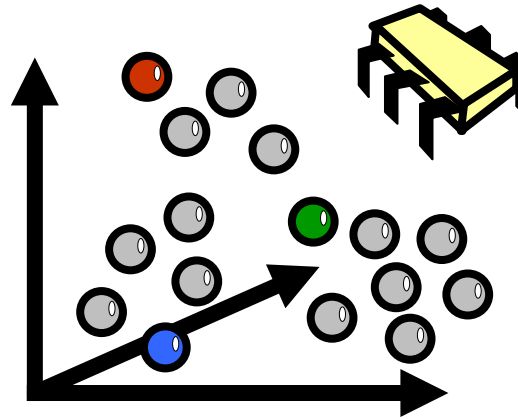
Each vector closer to those in same cluster than in different clusters!

# MapReduce

Split points among **mapping** threads



# MapReduce

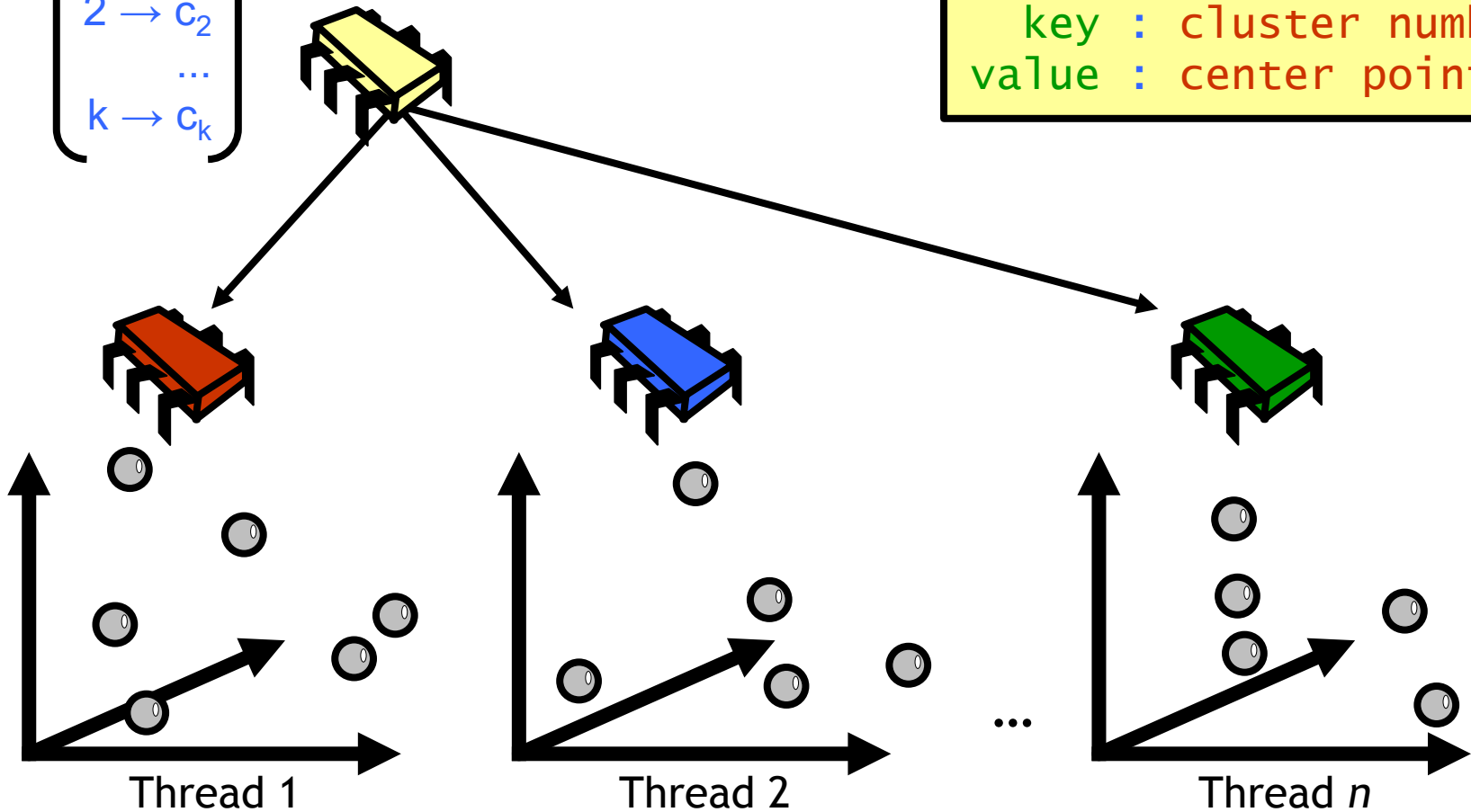


Reducer picks  $k$  “centers” at random

# Reducer

Reducer sends **key-value** pair to mappers

key : cluster number  
 value : center point

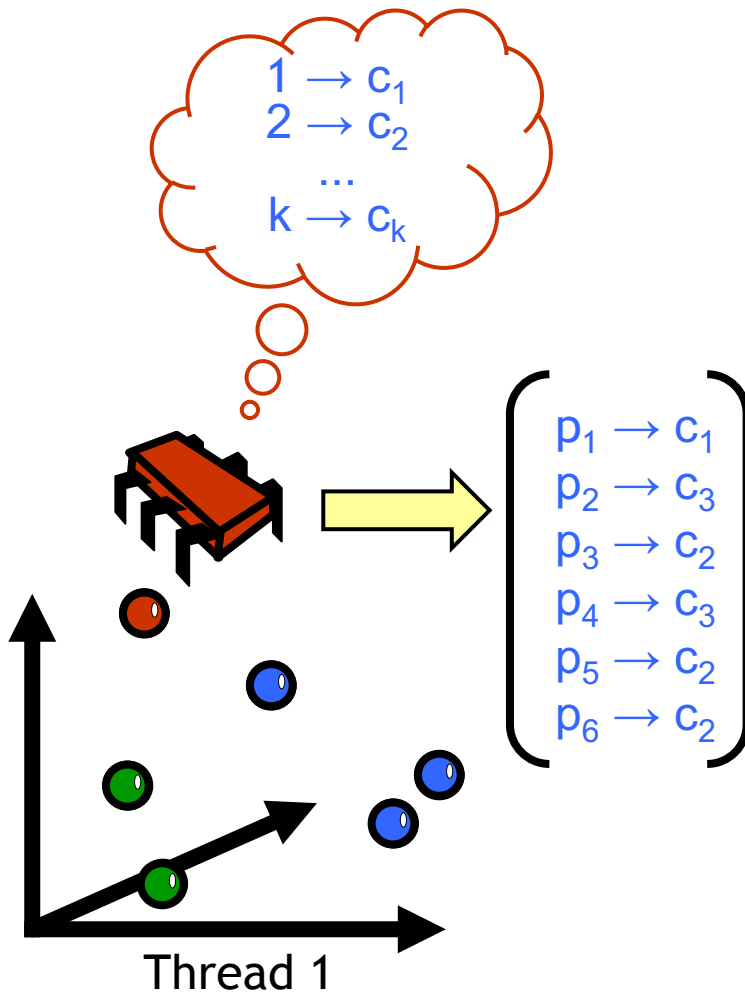
$$\begin{pmatrix} 1 \rightarrow c_1 \\ 2 \rightarrow c_2 \\ \dots \\ k \rightarrow c_k \end{pmatrix}$$


# Mappers

Each mapper uses centers to assign each vector to a cluster

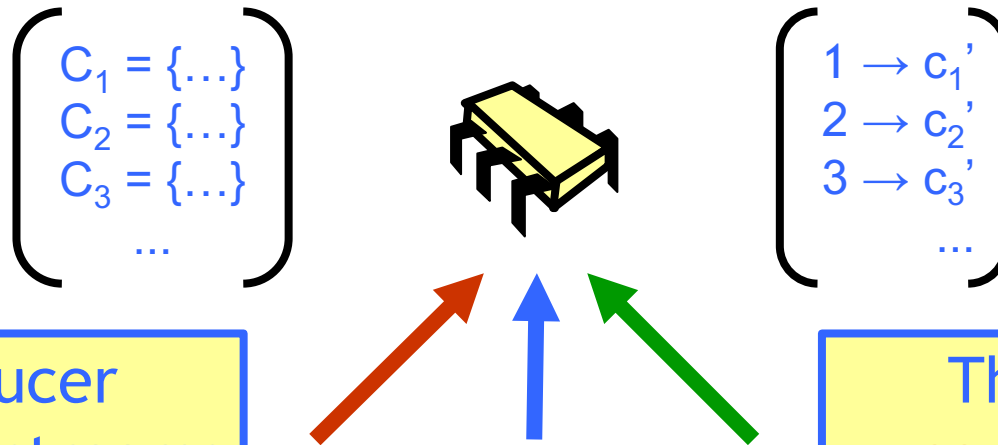
Mapper sends **key-value** stream to reducer

key : point  
value : cluster number





# Back at Reducer



The reducer merges the streams and **assembles clusters**

The reducer **computes new centers** based on new clusters

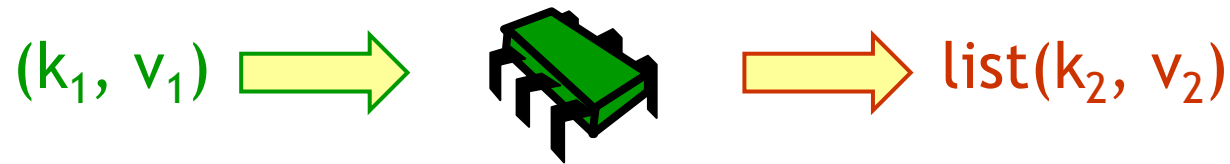
Once is not enough: reducer sends new centers to mappers

The process ends when centers become stable

# To Recapitulate

- We saw two problems...
  - Word count
  - K-means
- ...with similar solutions...
  - Map part is parallel
  - Reduce part is sequential
- ...that can applied to many other problems

# Map Function



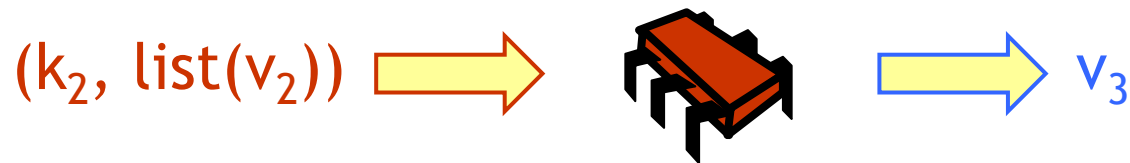
$(\text{doc}, \text{contents})$

$(\text{word}, \text{count})$

$(\text{cluster\#}, \text{center})$

$(\text{point}, \text{cluster\#})$

# Reduce Function



`(word, counts-list)`

`count`

`(cluster#, points-list)`

`new-cluster-center`

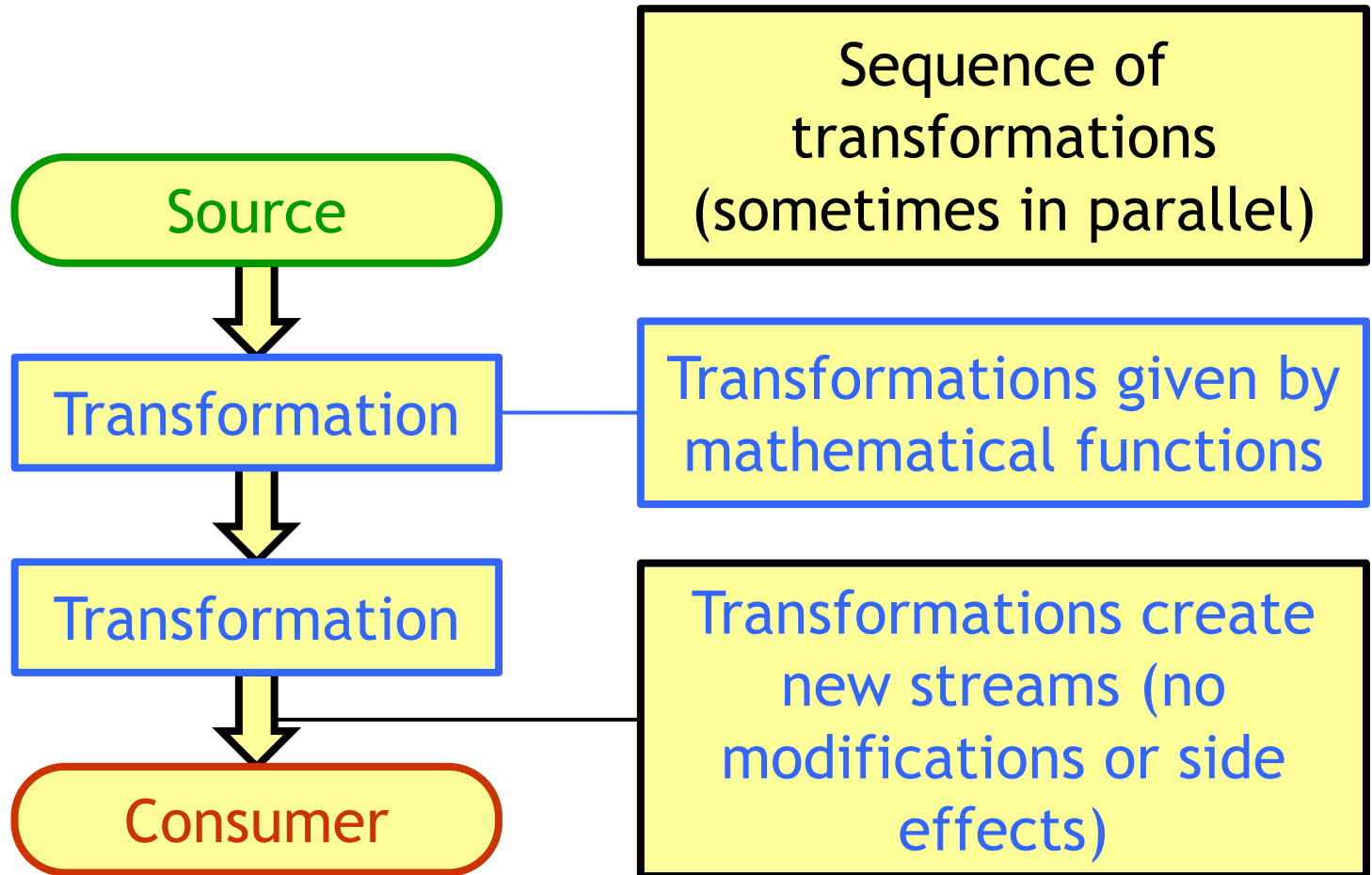
# Examples

- Distributed grep
  - **Map:** line of document
  - **Reduce:** copy line to display
- URL access frequency
  - **Map:** (URL, local count)
  - **Reduce:** (URL, total count)
- Reverse Web link graph
  - **Map:** (target link, source page)
  - **Reduce:** (target link, list of source pages)
- Page rank, matrix multiplication, histogram...

# Summary

- MapReduce is a generic solution for many problems
  - Map performs filtering and sorting
  - Reduce performs a summary operation
- Can be applied to different architectures
  - Distributed MapReduce on clusters
  - Multicore MapReduce with shared memory

# Streams

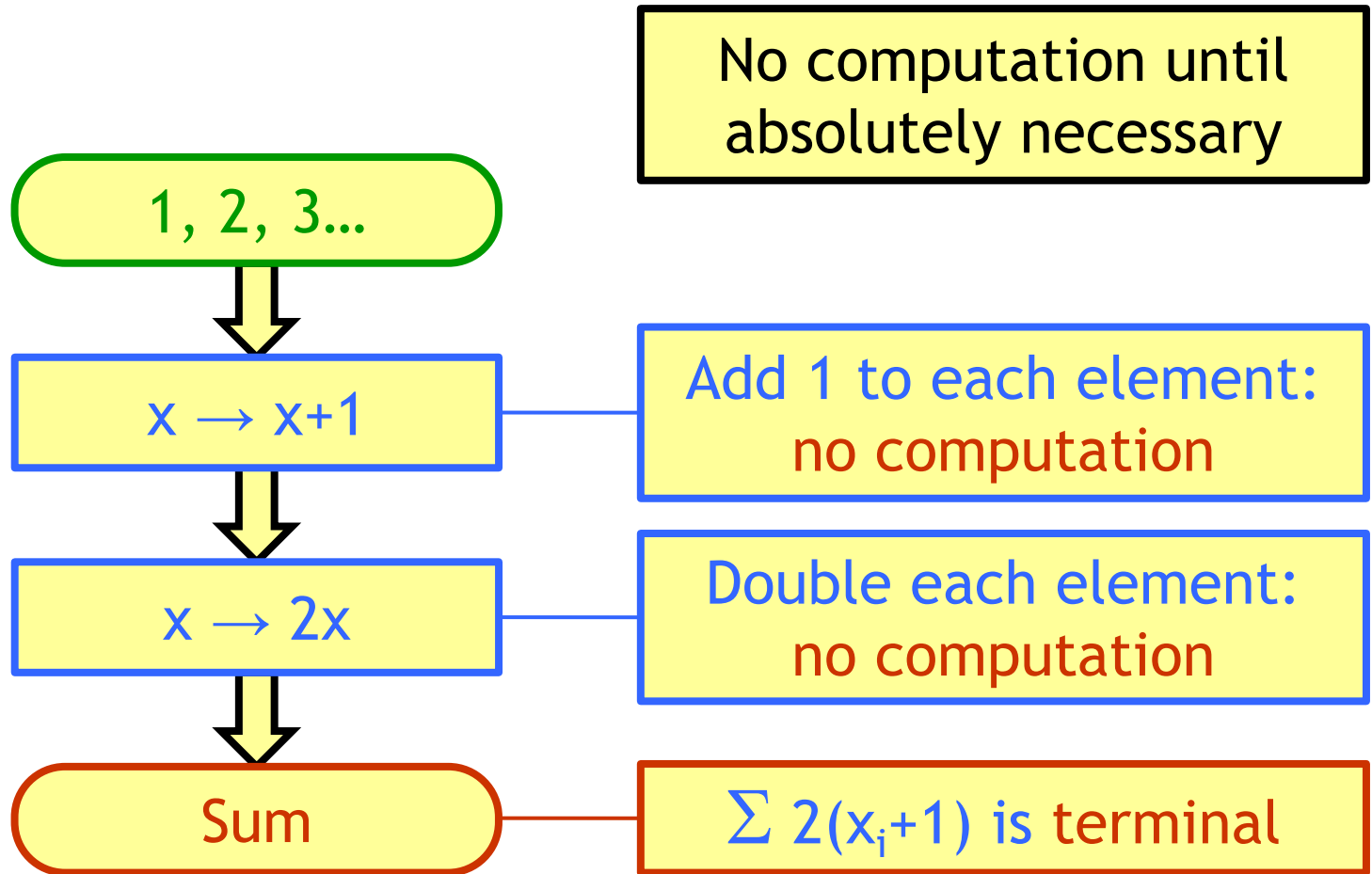


# Functional Programming

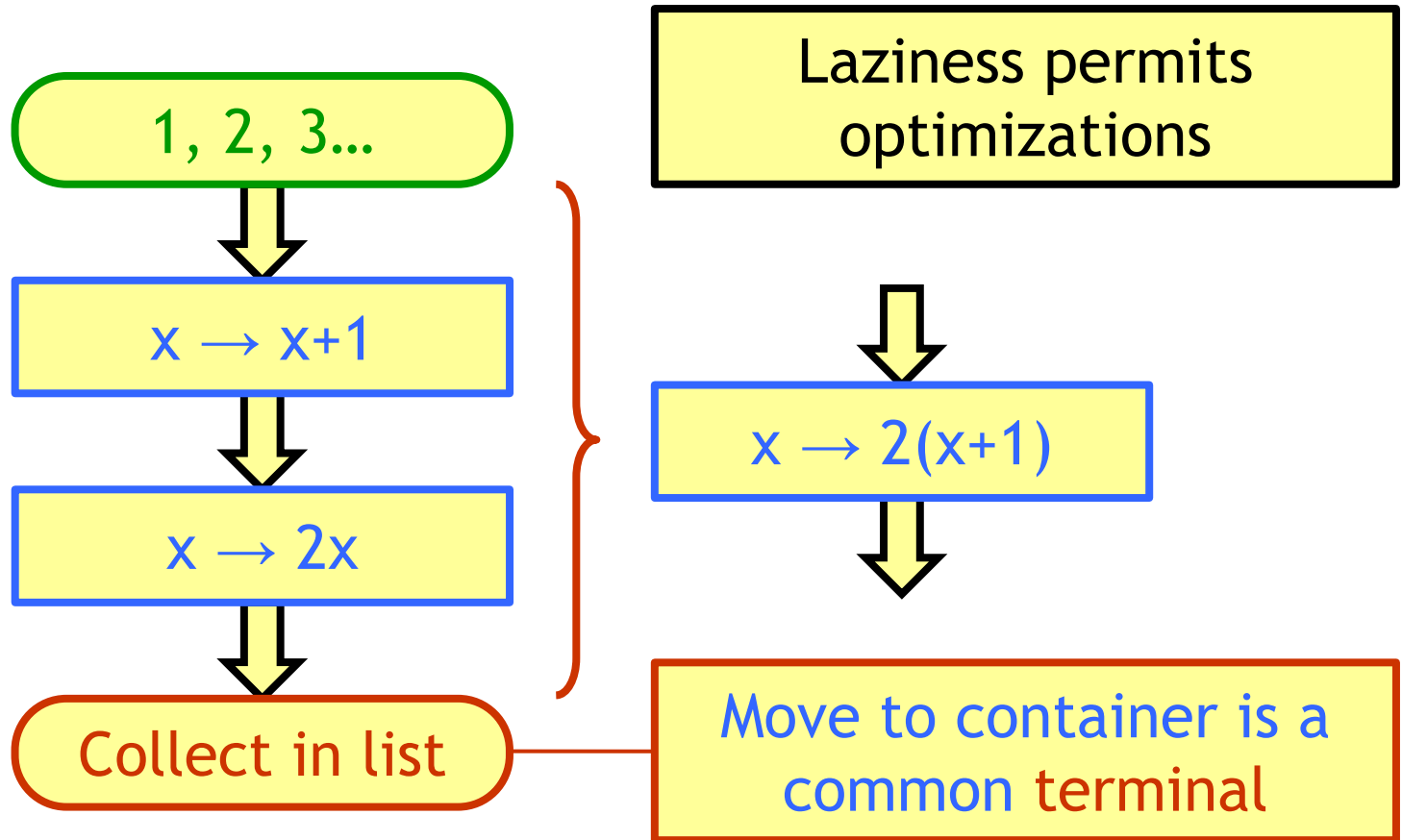
- Functions map old state to new state
  - Old state never changes
- No complex side effects
- Elegant, easier proof of correctness
- Isn't it too inefficient to be practical?



# Laziness



# Laziness



# Laziness

- Laziness permits infinite streams

```
Stream<Integer> fib = new FibStream();
```

1 1 2 3 5 8 13 21 34...

# Unbounded Random Stream

Unbounded stream of double-precision random numbers

```
Stream<Double> randomDoubleStream() {
    return Stream.generate(
        () -> random.nextDouble()
    );
}
```

Stream that generates new elements on the fly

Function to call when generating new element: Java lambda expression (anonymous method)

No loops  
 No conditionals  
 No mutable objects

# WordCount

Put each word from the document

`List<String> readFile(String fileName) {` into a list

...

`return reader` Open the file, create a `FileReader`

`.lines()` Turn the `FileReader` into a stream of lines, each line a string

`.map(String::toLowerCase)` (1)

`.flatMap(s -> pattern.splitAsStream(s))` (2)

`.collect(Collectors.toList());` (3)

}

(1) `map` creates a new stream by applying a function to each stream element (here: convert to lower case)

(2) `flatMap` replaces one stream element with multiple stream elements (here: split line into words)

(3) `collect` (terminal operation) puts stream elements in a container (here: in a list)

How a stream program looks: each line creates a new stream

No loops  
No conditionals  
No mutable objects

# WordCount

We have a list, now let's count words!

```
Map<String, Long> map = text
```

Start with list of words

```
    .stream()
```

Turn list into a stream

```
    .collect(
```

Put stream into a container (Map): word → count

```
        collectors.groupingBy(
```

Each element's key

```
            Function.identity(),
```

is that element

```
            collectors.counting()));
```

Each element's value is the number of times it appears

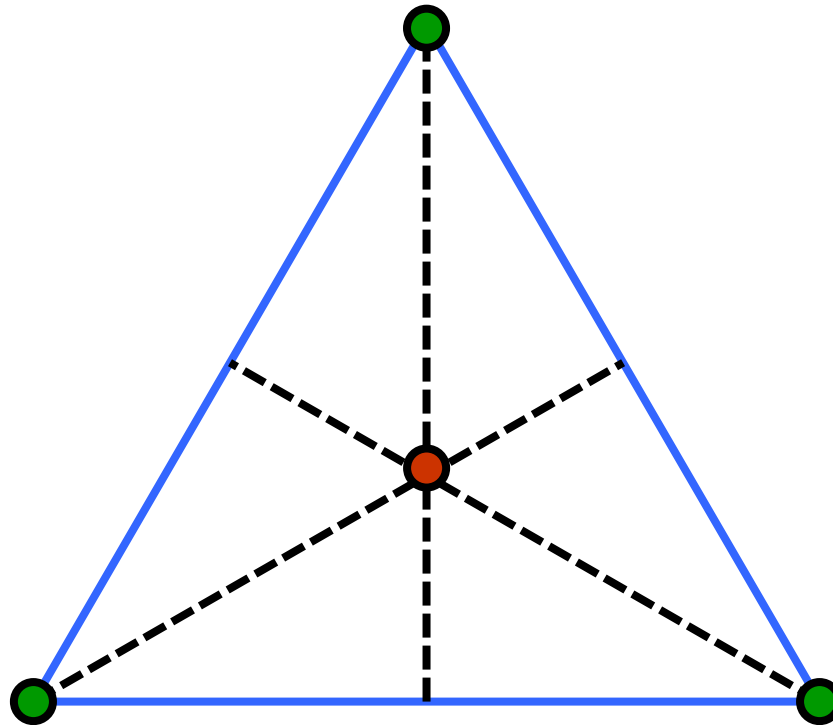
# K-Means

```
class Point {
    Point(double x, double y) {...}
    Point plus(Point other) {...}
    Point scale(double x) {...}
    static Point barycenter(
        List<Point> cluster
    ) {...}
}
```

Stream-based!

# Barycenter

The barycenter of a set of points is their center of mass





# K-Means Barycenter

```

Point barycenter(List<Point> cluster) {
    double numPoints = cluster.size();
    Optional<Point> sum = cluster
        .stream()
        .reduce(Point::plus);

    return sum.get()
        .scale(1 / numPoints);
}

```

Cluster size

Turn list into stream

# Reduce

`stream.reduce(+):`

$() \rightarrow \emptyset$

$(a) \rightarrow a$

$(a,b) \rightarrow a+b$

$(a,b,c) \rightarrow (a+b)+c$

*etc.*

Reduce is a  
terminal operation

# K-Means Barycenter

```

Point barycenter(List<Point> cluster) {
    double numPoints = cluster.size();
    Optional<Point> sum = cluster
        .stream()
        .reduce(Point::plus);
    return sum.get()
        .scale(1 / numPoints);
}
  
```

Sum points in cluster

Optional because sum might be empty!

Extract sum and divide by number of points

# K-Means

Read points from file

```
List<Point> points = readFile("cluster.dat");
```

```
centers = randomDistinctCenters(points);
```

Pick random centers

```
double convergence = 1.0;
```

```
while (convergence > EPSILON) {
```

Keep going until centers are stable

```
Map<Integer, List<Point>> clusters
```

```
= points.stream()
```

Turn list of points into stream

```
.collect(Collectors.groupingBy(
    p -> closestCenter(centers, p)));
```

```
...
```

Put each point in a map: **key** is closest center,  
**value** is list of points with that center

```
}
```

# K-Means

```

while (convergence > EPSILON) {
  ... Compute the new center (map: cluster# → center)
  Map<Integer, Point> newCenters = clusters
    .entrySet()
    .stream()
    .collect(
      Collectors.toMap(
        e -> e.getKey(),
        e -> Point.barycenter(e.getValue())
      ));
  convergence = distance(centers, newCenters);
  centers = newCenters;
}

```

Turn map into a stream of pairs:  
(cluster#, point)

Turn stream into a map:  
cluster# → barycenter

New key is still cluster number

New value is the barycenter computed earlier

If centers have moved, start again with the new centers

# Functional K-Means

- Many fewer lines of code
- Easier to read (really!)
- Easier to reason
- Easier to optimize

# Parallelism?

So far streams are sequential

```
Arrays.asList("Arlington",  
              "Berkeley",  
              "Clarendon",  
              "Dartmouth",  
              "Exeter")
```

Make list of strings and turn them into a stream

```
.stream()
```

forEach applies a method to each element (not functional)

```
.forEach(s -> printf("%s\n", s));
```

Output

```
Arlington  
Berkeley  
Clarendon  
Dartmouth  
Exeter
```

# Parallel Streams

We can use parallel streams

```
Arrays.asList("Arlington",
              "Berkeley",
              "Clarendon",
              "Dartmouth",
              "Exeter")
    .parallelStream() ➔ Turn list into parallel stream
    .forEach(s -> printf("%s\n", s));
```

Output

Diagram illustrating the output of parallel streams. Multiple overlapping boxes show the list of university names: Arlington, Berkeley, Clarendon, Dartmouth, and Exeter. The boxes are offset, representing concurrent processing. An ellipsis (...) follows the last box.



# Parallel Streams

A sequential stream can be made parallel

```
Arrays.asList("Arlington",
              "Berkeley",
              "Clarendon",
              "Dartmouth",
              "Exeter")
```

```
.stream()
.parallel()
```

Can turn stream into a parallel stream

```
.forEach(s -> printf("%s\n", s));
```

# Pitfalls

```
list.stream().forEach(
    s -> list.add(0)
);
```

Lambda (function) must not modify source!

```
source.parallelStream()
    .forEach(
        s -> target.add(s));
```

Exception if target not thread-safe

Order added is non-deterministic

# Summary

- Streams provide several benefits
  - Functional programming
  - Data parallelism
  - Compiler optimizations