

# Intro to Spark

**By Aaron Merlob** (edited and adapted to python by Ryan Henning)

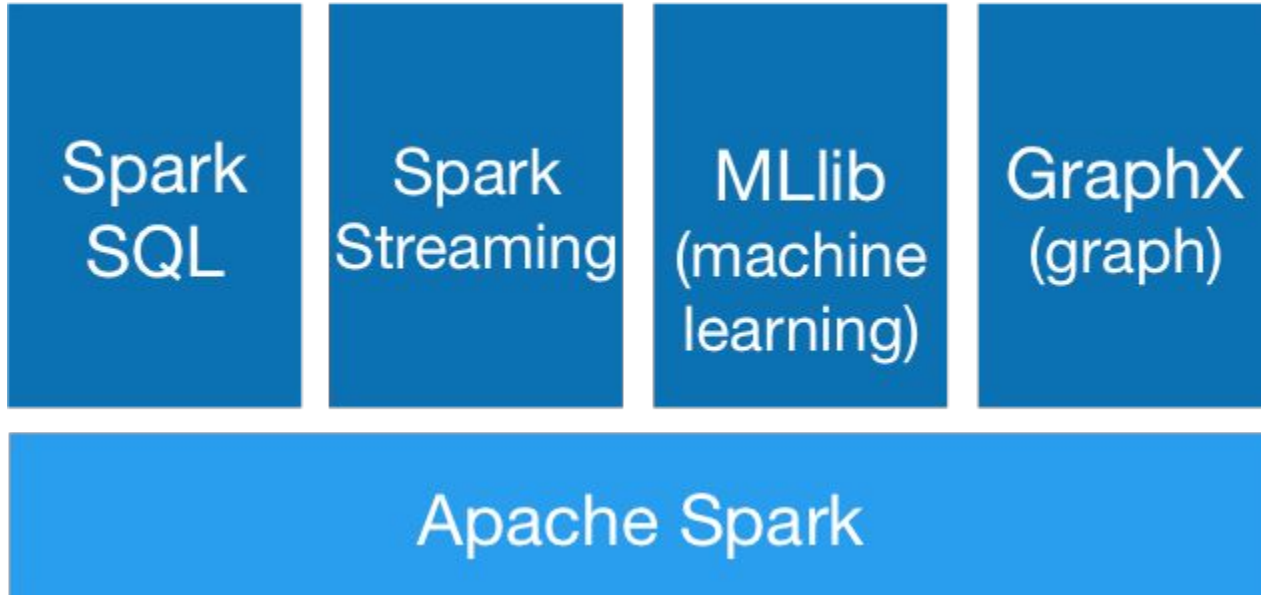
# Agenda

- About Apache Spark
- Resilient Distributed Dataset (RDD):
  - Features & Implementation
- Sample Functions:
  - Transformations and Actions
- Pair RDDs & More Sample Functions
- Code Samples & Mini-Quizzes

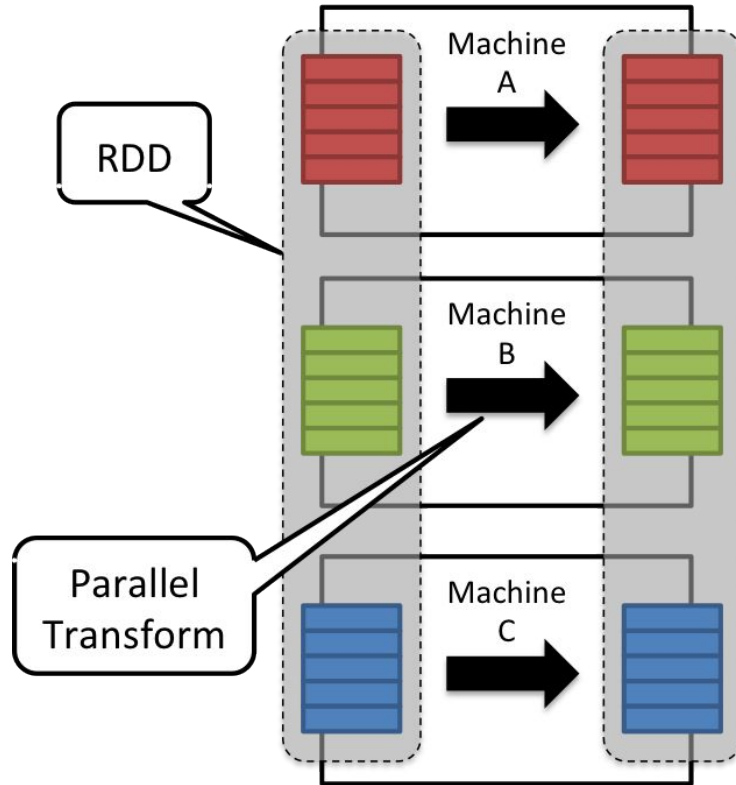
# Apache Spark

- Open-source cluster computing framework
- “Successor” to Hadoop MapReduce
- Supports Scala, Java, and Python and R!

# Spark Core + Libraries



# Resilient Distributed Dataset



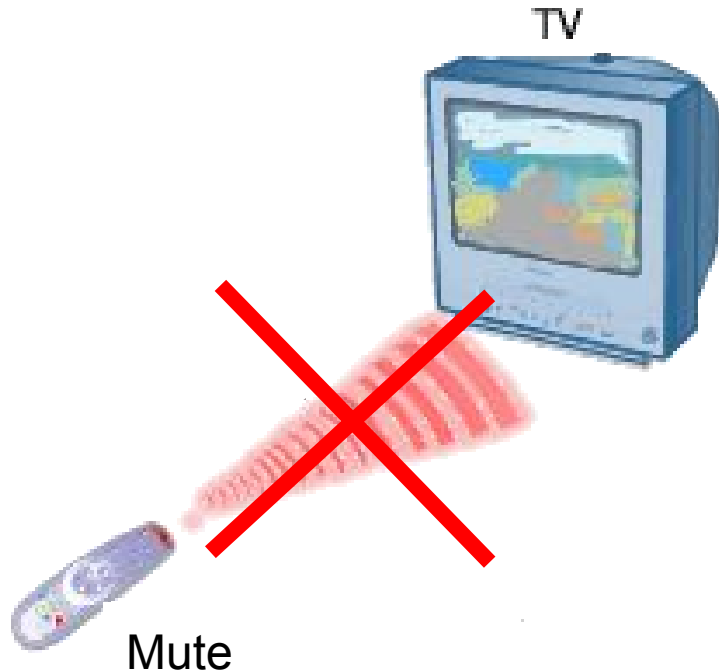
# RDD - Main Abstraction

Resilient Distributed Dataset (RDD)

- Distributed Collection
- Fault-tolerant
- Parallel operation - Partitioned
- Many data sources

... warning: bad puns coming (blame Aaron)

# RDDs are Immutable



**Immutable**

Lazily Evaluated

Cachable

# RDDs are Lazily Evaluated

How Good Is Aaron's Presentation?



Immutable

**Lazily Evaluated**

Cachable



# RDDs are Cachable



Immutable

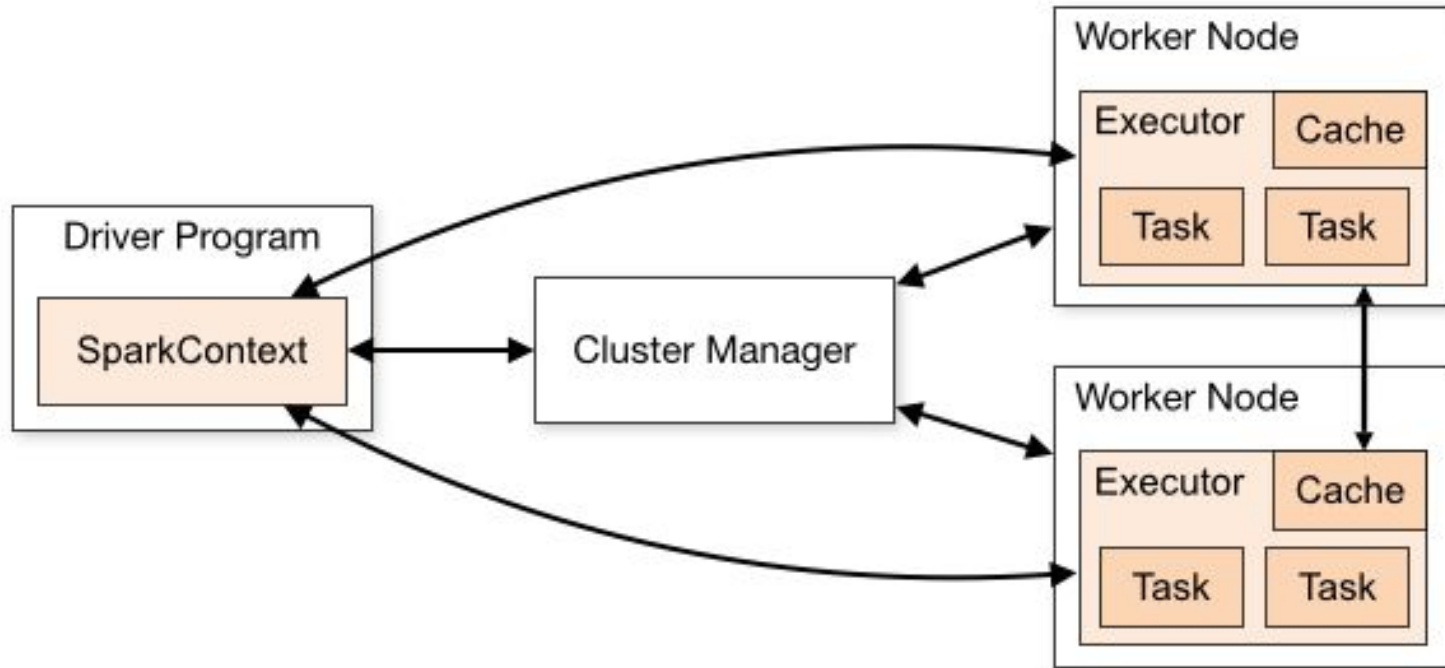
Lazily Evaluated

**Cachable**

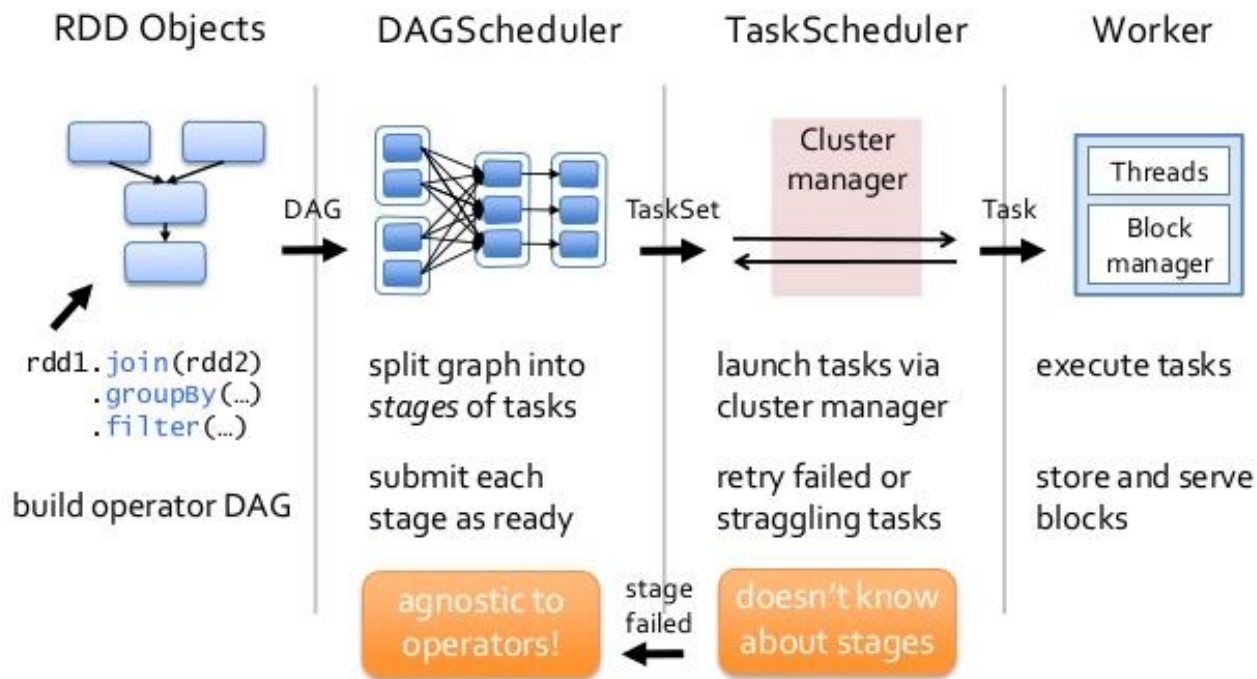
# Mechanical Sympathy

**“You don’t have to be an engineer to be a racing driver, but you do have to have Mechanical Sympathy.” – *Jackie Stewart, racing driver***

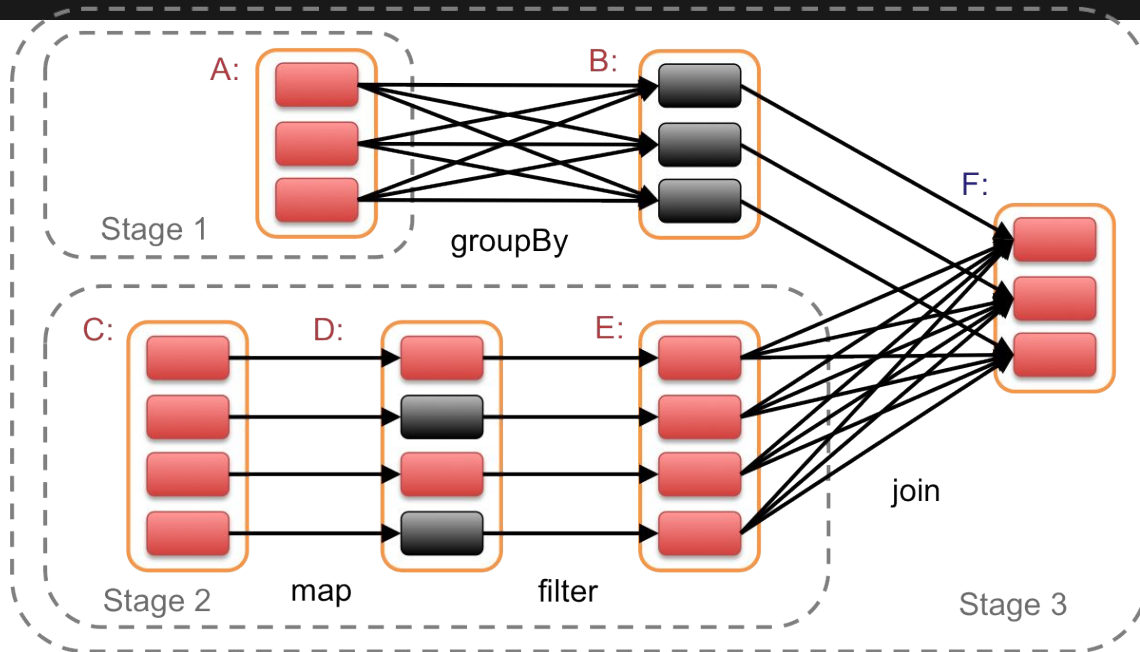
# Distributed Components



# Scheduler Process



# DAG Example



= RDD



= cached partition

# Two types of RDD Operations:



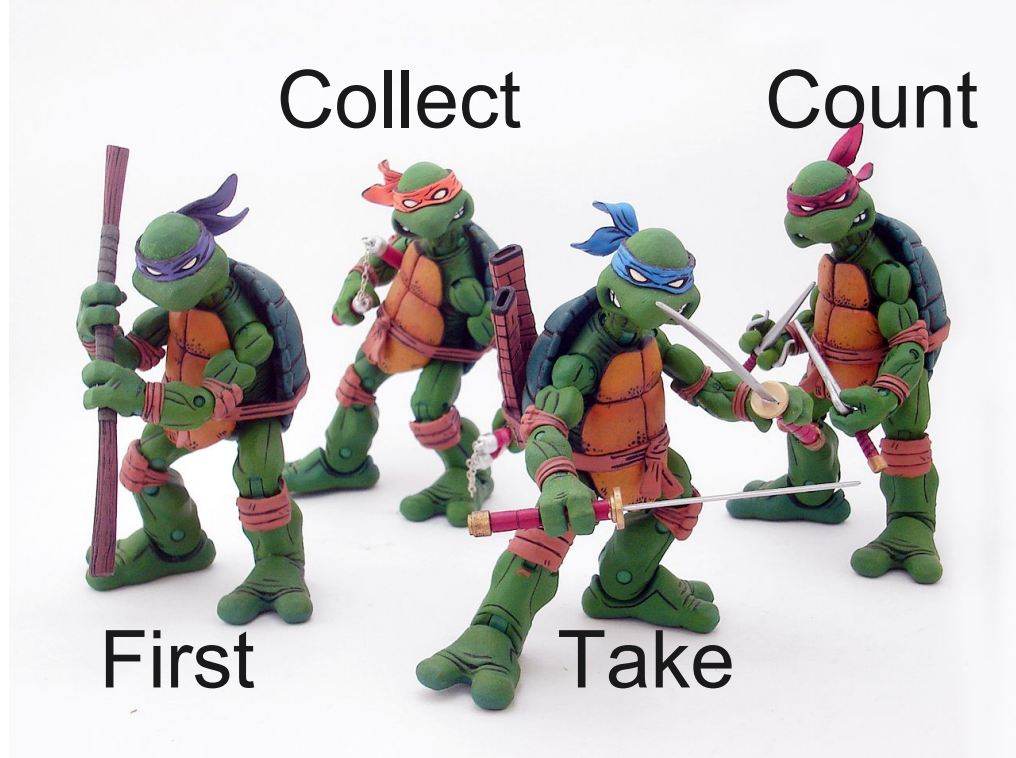
Transformations

Actions





# Four Actions



# Collect & Count

**Collect** - Return all the elements of the RDD as an array at the driver program.

**Count** - Return the number of elements in the RDD



# First & Take

**First** - Return the first element in the RDD

**Take** - Return an array with the first  $n$  elements of the RDD

# 3 Transformations

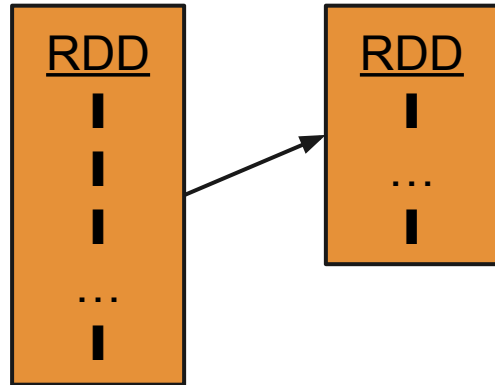
- Filter
- Map
- FlatMap



# RDD.filter

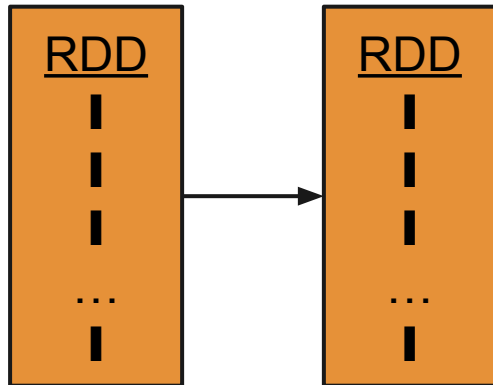
Applies a function to each element

Returns elements that evaluate to true



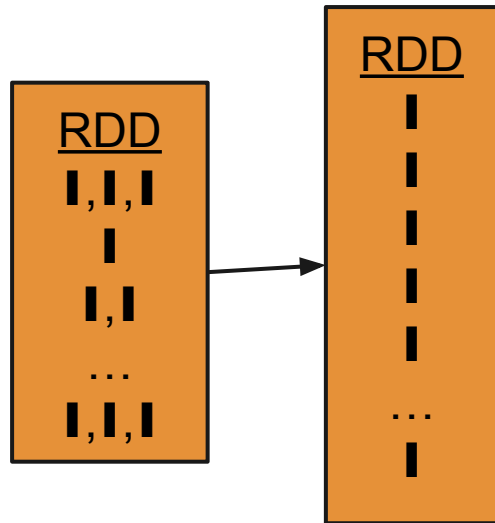
# RDD.map

- Transforms each element
- Preserves # of elements



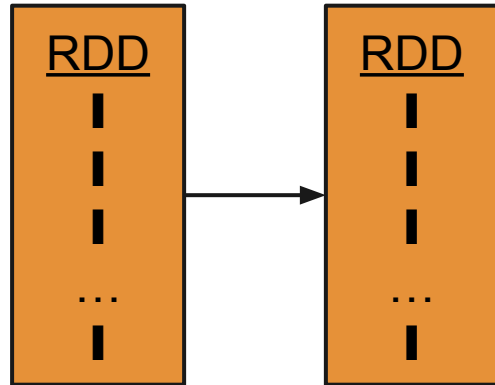
# RDD.flatMap

- Transforms each element into 0-N elements
- Changes # of elements



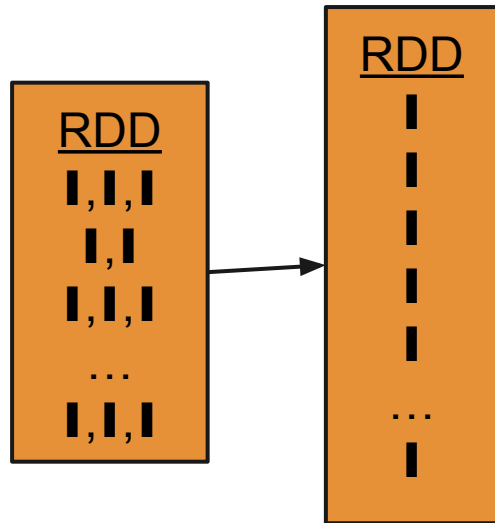
# Map vs FlatMap - Examples

Alphabet letters (A,B,C) to  
NATO Phonetic Letters (Alfa, Bravo, Charlie)



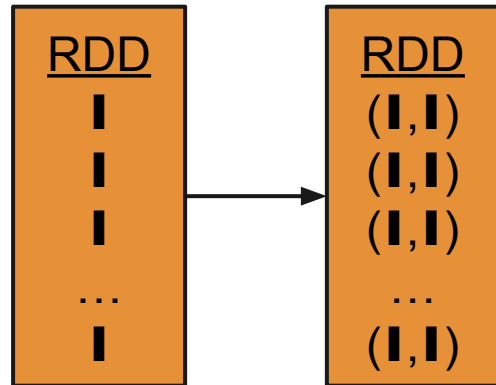
# Map vs FlatMap - Examples

Paragraph of words (“Mary had a little lambda”) to individual words



# Map vs FlatMap - Examples

Numbers  $x$ , transform to the tuple  $(x, x^2)$





# Pair RDDs

Operations on tuples (key, value)

Offers better partitioning

Exposes new functionality

# Reduce & ReduceByKey

- **Reduce** (Action)

Aggregate RDD elements using a function

Returns single element

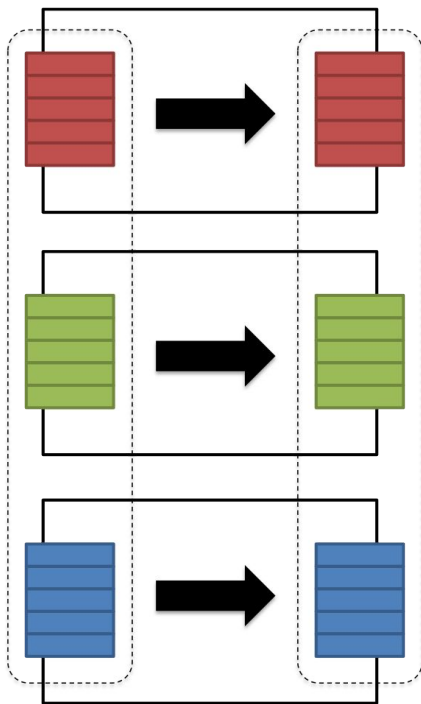
- **ReduceByKey** (Transformation)

Aggregate Pair RDD elements using a function

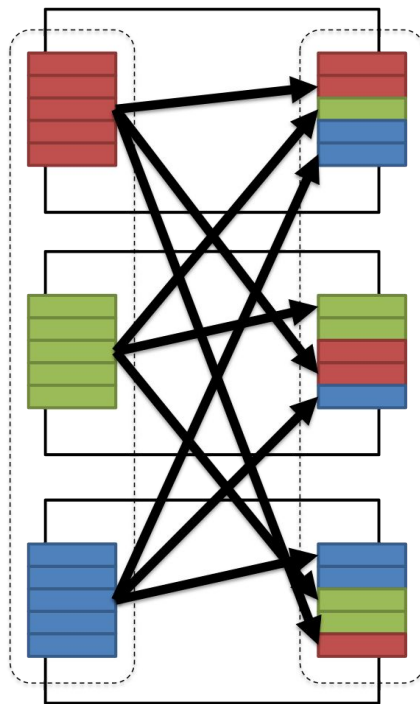
Returns Pair RDD

# Transformation Complexity

Narrow transformation



Wide transformation



# Code Examples (python)

## Map, Collect:

```
data = sc.parallelize([1, 2, 3])  
mapped_data = data.map(lambda x: x**2)  
x = mapped_data.collect()
```

What is x's value and type?

# Code Examples (python)

## FlatMap, Take:

```
data = sc.parallelize([1, 2, 3])  
flat_data = data.flatMap(lambda x: range(0, x))  
x = flat_data.take(4)
```

What is x's value and type?

# Code Examples (python)

## Reduce, Count:

```
data = sc.parallelize([1, 2, 3])  
flat_data = data.flatMap(lambda x: range(0, x))  
c = flat_data.count()  
r = flat_data.reduce(lambda a, b: a + b)
```

What is c's value and type?  
What is r's value and type?

# Pop Quiz

What is the 'sc' in `sc.parallelize()`?

SparkContext.

- Given to you when you launch Spark shell
- Your way to get data into/out of RDDs

# Transformation vs. Action?

```
data = sc.parallelize( \  
    ["Aaron Merlob", "Ryan Henning", "Aaron Ryan", ""])  
words = data.flatMap(lambda s: s.split(" "))  
result = words.map(lambda w: (w, 1)) \  
    .reduceByKey(lambda a, b: a + b)  
result.filter(lambda p: 'a' in p[0]).count()  
result.filter(lambda p: p[1] > 1).count()
```

We do  
redundant  
work right  
here!





# Transformation vs. Action?

```
data = sc.parallelize( \
    ["Aaron Merlob", "Ryan Henning", "Aaron Ryan", ""])
words = data.flatMap(lambda s: s.split(" "))
result = words.map(lambda w: (w, 1)) \
    .reduceByKey(lambda a, b: a + b).cache()
result.filter(lambda p: 'a' in p[0]).count()
result.filter(lambda p: p[1] > 1).count()
```

This  
prevents  
the  
redundant  
work.

# What did we learn?

- Spark coordinates multiple computers.
- RDDs are immutable and lazily evaluated.
- Transformations build a plan of attack (DAG).
- Actions force an evaluation (produce answers).
- Developers designate what they want to cache!
- The Spark shell gives you a SparkContext ('sc').

# Live Demo

With ``pyspark`` shell. It creates the `SparkContext (sc)` for you!

With `iPython` notebook. You'll have to create the `SparkContext` yourself.

(Unless you do fancy things with `iPython` notebook...)

# tmux

Live demo...

# APPENDIX

# Type Inferred - Comparison

**Python shell:**

```
numbers = sc.parallelize([1,2,3])
```

```
letters = sc.parallelize(["a","b","c"])
```

```
numbers.map(lambda x: x * x).collect()
```

```
letters.map(lambda x: x * x).collect()
```

**Fails at runtime**

# Type Inferred - Comparison

## Scala shell:

```
val numbers = sc.parallelize(Seq(1,2,3))  
val letters = sc.parallelize(Seq("a","b","c"))  
numbers.map(x => x * x).collect()  
letters.map(x => x * x).collect()
```

**Fails at compile-time**