Verification Problems in SPARK Programs

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What is Apache SPARK?

- SPARK is a more recent platform for large-scale data parallel processing.
- To reduce I/O overhead, SPARK is memory-based.
  - Keep intermediate results in memory;
  - Recompute results upon faults.
  - Google MAPREDUCE is disk-based.
- To avoid unnecessary computation, SPARK is lazy.
  - Computation is performed when necessary.
  - Think of lazy evaluation in purely functional languages such as Haskell.

Why Apache SPARK? I

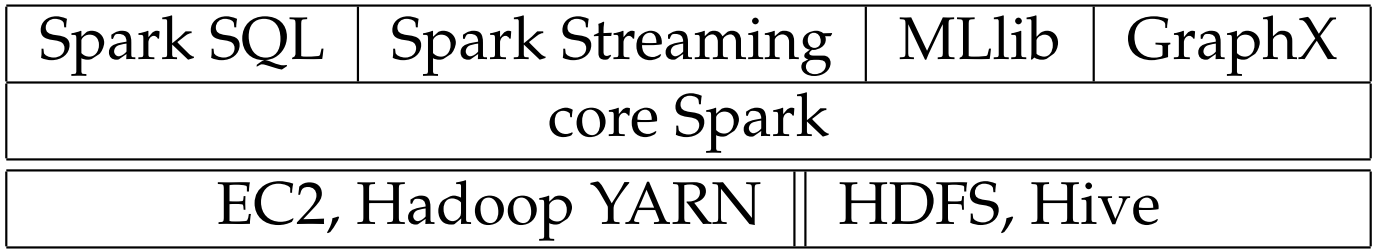
- SPARK is still under (very) active development.
- It has lots of applications.
  - Go to databricks for more information.
- It is an easy-to-use distributed computing environment.
- Many distributed programs are developed and executed.

Why Apache SPARK? II

- Programming in SPARK is so simple that novice programmers are writing distributed SPARK programs.
- Concurrent programs are easy to have tricky bugs.
- I believe this is a good opportunity for verification!
  - We can make impacts on SPARK development.
  - We can verify distributed SPARK programs.
  - We can contribute to big data researches.

Plan

SPARK Architecture



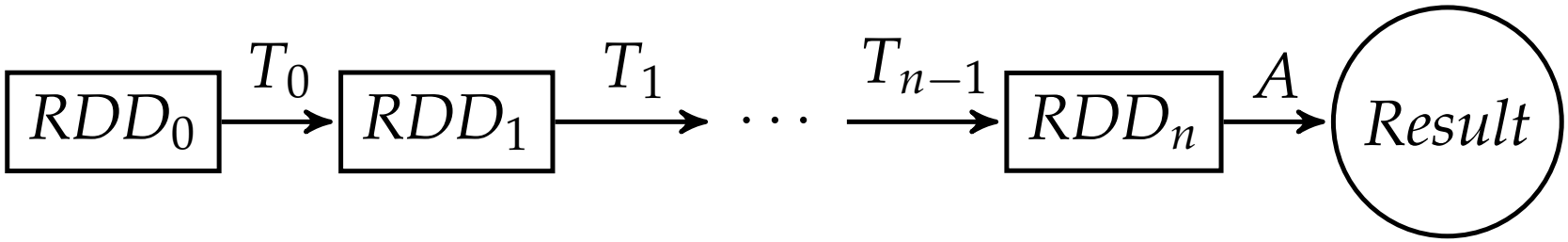
- SPARK runs on top of distributed process/data clusters.
  - EC2, Hadoop YARN manage distributed processes.
  - HDFS, Hive manage distributed data.
- Core Spark provides basic APIs for distributed data processing.
- On top of core Spark, four libraries are available:
  - Spark SQL: database queries
  - Spark Streaming: streaming data processing
  - MLlib: machine learning library
  - GraphX: pregel-like graph library

SPARK Programming Model I

- A distributed collection of data items is a *Resilient Distributed Dataset (RDD)*.
- A SPARK program creates an RDD from raw data stored in the underlying distributed file system.
- A SPARK program computes by processing data items in RDDs.

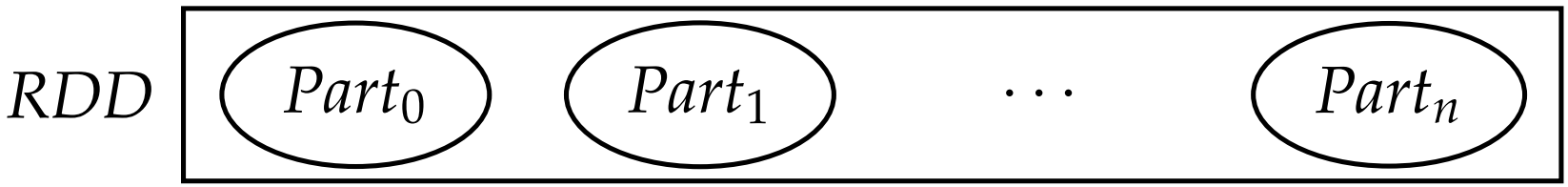
SPARK Programming Model II

- An RDD can be changed into another RDD through *transformation*.
- Data in an RDD can be collected through *actions*.
- Typically, a SPARK program performs a sequence of transformations then followed by an action on an RDD.



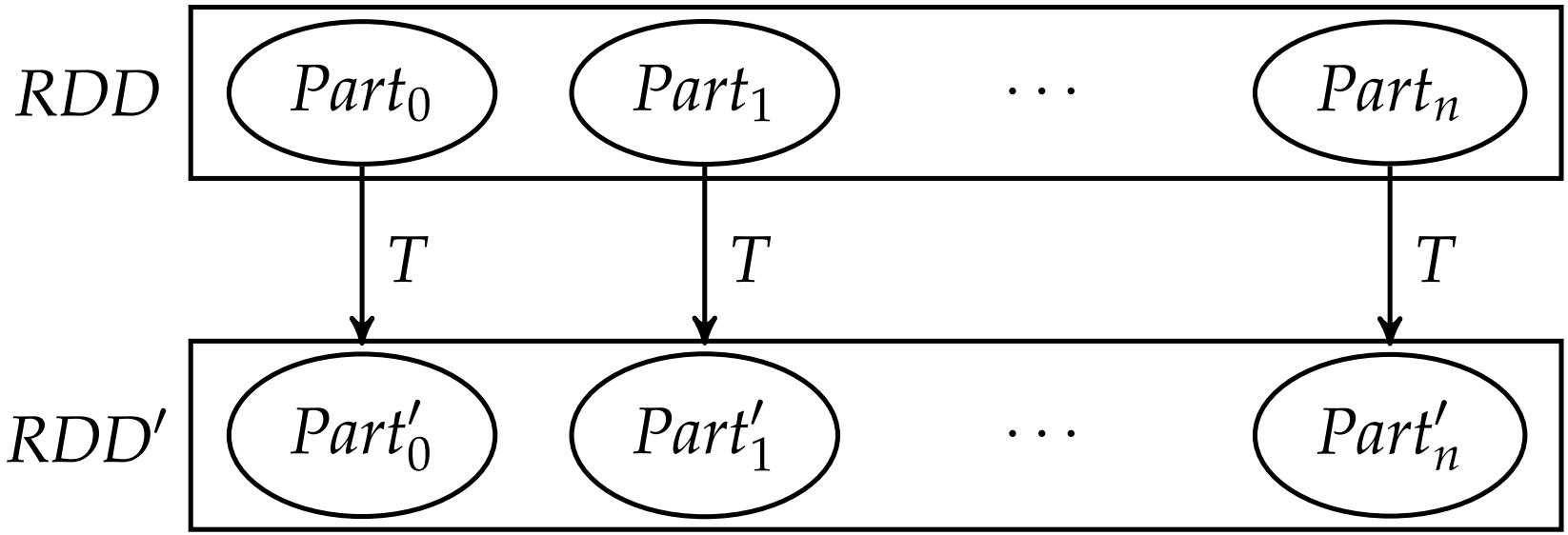
Distributed Data Processing I

- An RDD consists of several *partitions*.
- A partition is a basic block of data items.
  - It is stored in a *worker* node of the underlying cluster.
  - Computation on a partition is local.



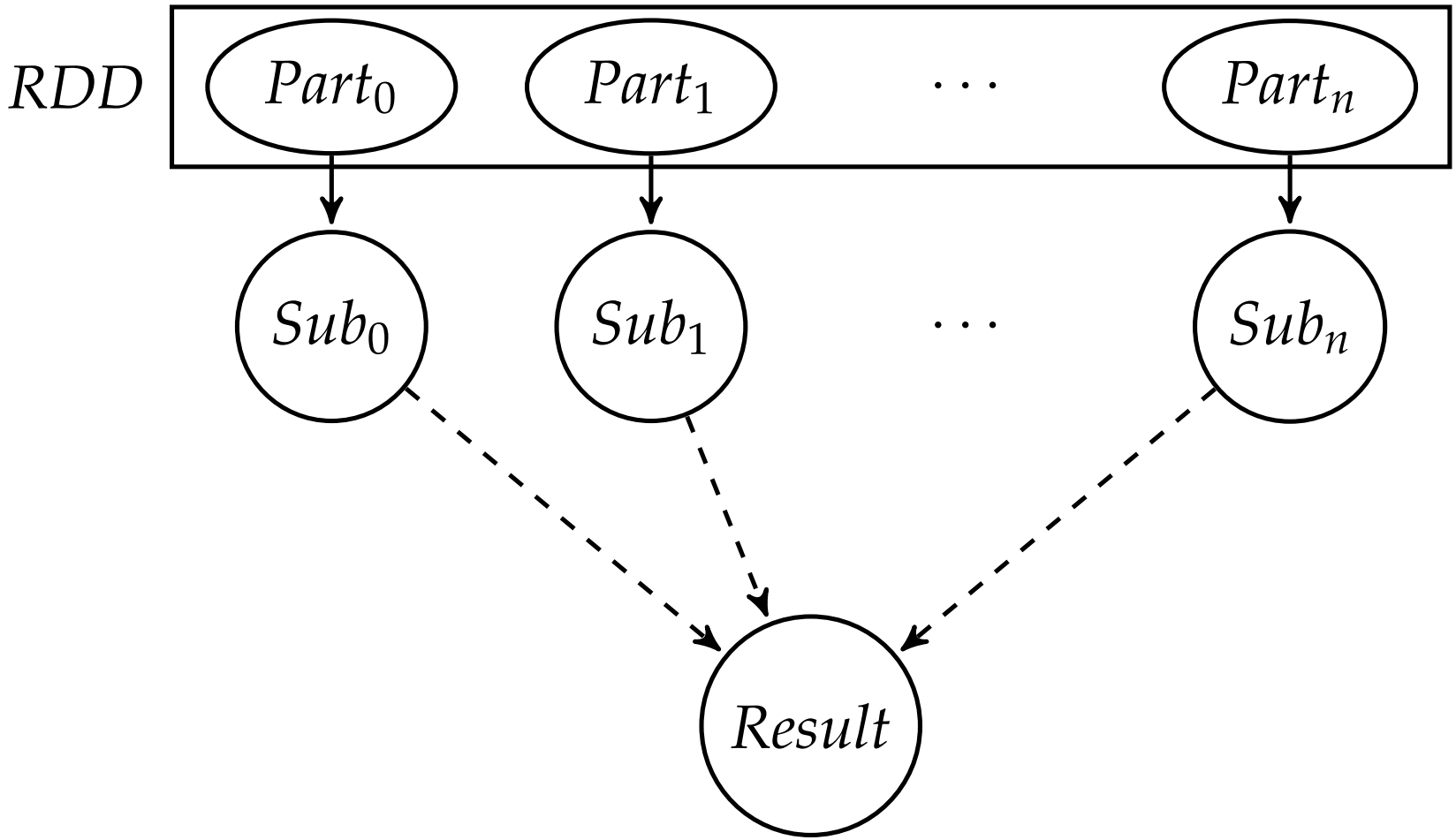
Distributed Data Processing II

- A transformation is hence performed locally and distributively.



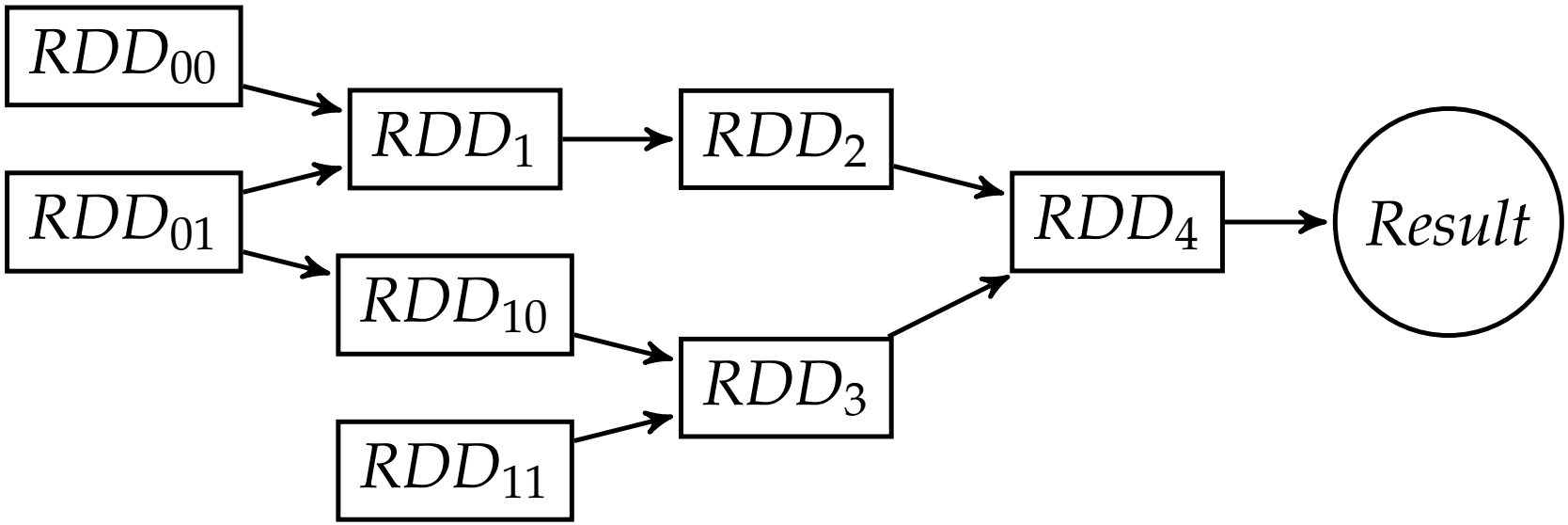
Distributed Data Processing III

- An action however requires local computation followed by communication with the *master* node.



Distributed Data Processing IV

- In practice, data flow can be complicated.
- SPARK takes care of job scheduling, message passing, and even fault tolerance automatically.
- Programmers only specify local computation.



Abstract Functional Model for SPARK I

- We are interested in functional behaviors of SPARK programs.
- To simplify our discussion, an abstract functional model for SPARK will be used.
- Our abstract model ignores implementation details (performance, fault tolerance, etc) but focuses on functional behaviors.

Abstract Functional Model for SPARK II

- A partition is modeled by a list.
- For instance, a partition of data items `0`, `1`, `2` is modeled by the list `[0, 1, 2]`.
- In general, a partition consisting of data items of the type α is modeled by a list of the type `[`α`]`.
- Define

$$\texttt{type Partition } \alpha \texttt{ = [}\alpha\texttt{]}$$

Abstract Functional Model for SPARK III

- An RDD is a sequence of partitions.
- Hence an RDD is modeled by a list of partitions.
- That is, an RDD consisting of data items of the type α is modeled by a list of the type `[Partition` α`]`.
- Similarly, define

$$\texttt{type RDD } \alpha \texttt{ = [Partition } \alpha \texttt{]}$$

Abstract Functional Model for SPARK IV

- A transformation transforms an RDD into another RDD.
- Consider the transformation `map` as an example.
- Given a function from α to β, `map` transforms an RDD whose data items are of the type α to another RDD whose data items are of the type β.
- That is, we have

$$\texttt{[RDD } \alpha \texttt{].map} \ :: \ (\alpha \to \beta) \to \texttt{RDD } \beta$$

- The functional specification of `map` is straightforward for functional programmers.
  - Exercise!

Abstract Functional Model for SPARK V

- An action returns a result by collecting data items in an RDD.
- Consider the action `reduce` as an example.
- Given a function from $(\alpha \times \alpha)$ to α, `reduce` reduces an RDD whose data items are of the type α to a value of the type α.
- That is,

$$\texttt{[RDD } \alpha \texttt{].reduce} \ :: \ (\alpha \times \alpha \to \alpha) \to \alpha$$

- Again, the functional specification is straightforward.
  - Another exercise!

Abstract Functional Model for SPARK VI

- We have the functional specification of SPARK transformations and actions.
- Our specification is in Haskell and Scala.
- We uses the executable specification to develop a distributed randomized graph coloring SPARK program.

Word Counts I

- Writing distributed programs is easy in SPARK.
- Consider the SPARK program for word counts from its tutorial.

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
```

Word Counts II

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
```

- `sc.textFile` reads a text file and returns an RDD whose data items are strings.
- `flatMap`, `map`, and `reduceByKey` are transformations.

Word Counts III

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
```

- Let us read the code by types in our functional specification.

$$\texttt{textFile} \;::\; \texttt{String} \to \texttt{RDD String}$$

$$\texttt{[RDD } \alpha\texttt{].flatMap} \;::\; (\alpha \to \texttt{[}\beta\texttt{]}) \to \texttt{RDD } \beta$$

- `textFile` is an RDD of strings. Each string is a line in the file.
- `flatMap` maps a line to a list of strings and then flattens all lists.
- We have an RDD of strings. Each string is a word in the file.

Word Counts IV

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
```

- For each string in the RDD, we map it to a pair of the string and `1`.

$$\texttt{[RDD } \alpha\texttt{].map} :: (\alpha \to \beta) \to \texttt{RDD } \beta$$

$$\texttt{[RDD } (\alpha \times \beta)\texttt{].reduceByKey} :: (\beta \times \beta \to \beta) \to \texttt{RDD } (\alpha \times \beta)$$

- For each string appeared in a pair, we reduce the associated integers by summation.

Word Counts V

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
```

- Finally, we have

$$\texttt{wordCounts} :: \texttt{RDD}\ (\texttt{String} \times \texttt{Int})$$

- Each string is associated with exactly an integer.
- The associated integer is the number of occurrences of the string in the file.

Lazy Evaluation

- Notice that a sequence of transformations are performed in word counts without any action.
- By lazy evaluation, SPARK will not perform any computation.
  - SPARK returns immediately after the program is entered.
- The computation will be carried out only when concrete values are needed.
- For example, we can count the number of words by

```
wordCounts.reduce(((_, u), (_, v)) => ("", u+v))
          ._2                        // (a, b)._2 = b
```

- Or, we can ask SPARK to compute an array of data items by

```
wordCounts.collect()
```

More SPARK Libraries

- Several libraries are built on top of core SPARK.
- The SPARK GraphX library is a framework for implementing distributed graph algorithms.
- In GraphX, a graph is represented by two RDDs:
  - a vertex RDD contains vertices;
  - an edge RDD contains edges.
- It also has a pregel-like interface for distributed iterative computation over graphs.
- We have interns to implement a handful of distributed graphs algorithms in GraphX during this summer.
  - Correctness?

Plan

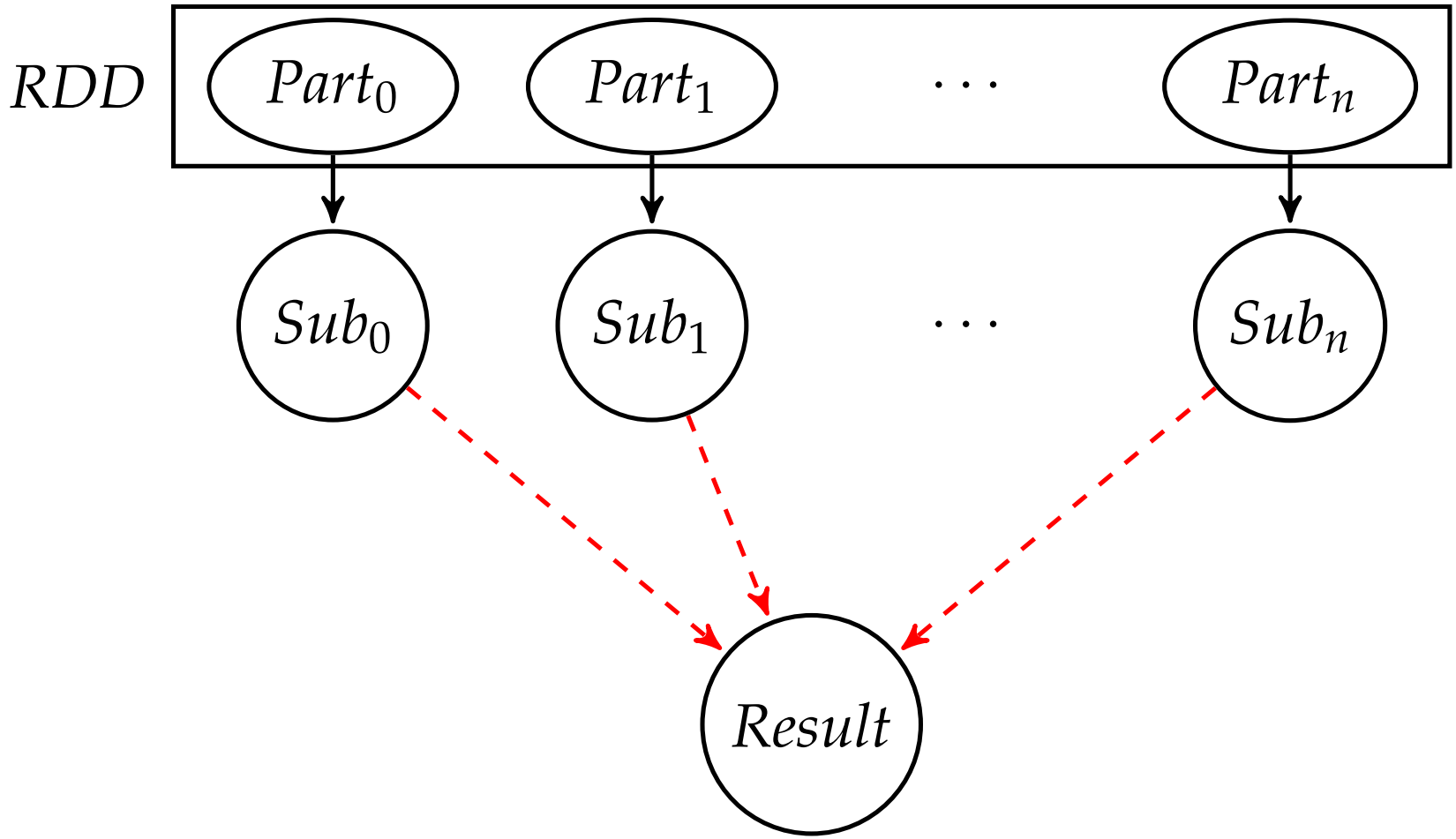
All Look Good

```
val textFile = sc.textFile("README.md")
val wordCounts =
      textFile.flatMap(line => line.split("␣"))
              .map(word => (word, 1))
              .reduceByKey((a, b) => a + b)
wordCounts.reduce(((_, u), (_, v)) => ("", u+v))
          ._2
```

- Observe that SPARK programmers only specify local computation in transformations and actions.
- It is easy to write distributed SPARK programs.
- So what can go wrong?

Peeking Under the Hood

- Similar to MAPREDUCE, concurrency makes computation non-deterministic.



Requirements of Local Computation I

- Due to concurrency and efficiency, SPARK computation is inherently non-deterministic.
- What we look for is deterministic *outcomes*.
- That is, the results will be the same for all non-deterministic computation.

Requirements of Local Computation II

- To ensure deterministic outcomes, SPARK requires certain algebraic properties on local computation.
- For instance, the documentation of the action `reduce` says:

  > "Reduces the elements of this RDD using the specified commutative and associative binary operator."

- In the word counts example, the binary operator is both associative and commutative.
  - `((_, u), (_, v)) => ("", u+v)`

Algebraic Properties I

- Let $\oplus :: \alpha \times \alpha \to \alpha$ be a binary operator.
- $\oplus$ is associative if for every x, y, z

$$(x \oplus y) \oplus z = x \oplus (y \oplus z).$$

- $\oplus$ is commutative if for every x, y

$$x \oplus y = y \oplus x.$$

- 0 is a neutral element of $\oplus$ if for every x

$$x \oplus 0 = 0 \oplus x = x.$$

- These algebraic properties are required for various SPARK actions.

Algebraic Properties II

- More generally, consider any universally quantified equations over functions and constants.

$$\begin{aligned} t \quad ::= \quad & x \mid c \mid f(t, \ldots, t) \\ & \forall \overline{x}.\, t = t \end{aligned}$$

- Distributive law

$$\forall x, y, z.\, x \otimes (y \oplus z) = (x \otimes y) \oplus (x \otimes z)$$

- Idempotent unary function

$$\forall x.\, f(f(x)) = f(x)$$

- Can we prove such algebraic properties hold for SPARK operators?

SPARK Operators in Practice I

- Abstractly, algebraic properties are easy to specify.
- Their concrete interpretations necessarily depend on SPARK operators in practice.
- We divide SPARK operators into three classes:
  - numerical operators;
  - abstract data operators;
  - arbitrary user-defined operators.

SPARK Operators in Practice II

- Algebraic properties over numerical SPARK operators are straightforward to interpret.
- They are just different from mathematical operators.
- Mathematical addition and multiplication are both associative and commutative.
- SPARK programs rarely use exact mathematical addition and multiplication.
- For bounded integers, are $+$ and $*$ still associative and commutative?
- For floating-point numbers, are $+$ and $*$ still associative and commutative?

SPARK Operators in Practice III

- Abstract data types are employed in SPARK programs.
- Their operations are often used in transformations and actions.
- Consider the union operator `U` for the data type `Set[`α`]`.
- We know the set-theoretic union $\cup$ is associative and commutative.
- Do we really have, say, `A U B` = `B U A`?
- Probably not. The concrete data structure for `A U B` is likely to be different from `B U A`.
- What do we mean (and show) that `U` is commutative?

SPARK Operators in Practice IV

- For user-defined SPARK operators, interpretations of algebraic properties are even less clear.
- They may not correspond to any abstract objects.
- What do we mean (and show) that such operators satisfy certain algebraic properties?

Classical Techniques for Abstract Data Types I

- When we prove the correctness of data type implementations, similar problems arise.
- Let `U` be an implementation of the set-theoretic union $\cup$.
- How do we show that `U` is correct?
- Tony Hoare came up with a solution back in 1972.

Classical Techniques for Abstract Data Types II

- Let $\mathcal{A}$ be a *representation function* mapping any concrete set `S` to an abstract set S.
- To show `U` is correct, it is to show

$$\mathcal{A}(\texttt{A U B}) = \mathcal{A}(\texttt{A}) \cup \mathcal{A}(\texttt{B})$$

for every concrete sets `A` and `B`.

Classical Techniques for Abstract Data Types III

- The representation function lifts concrete structures to abstract objects.
- Using a representation function, it is clear how to verify algebraic properties.
- For example, `U` is commutative if for every `A` and `B`

$$\mathcal{A}(\texttt{A U B}) = \mathcal{A}(\texttt{B U A}).$$

Classical Techniques for Abstract Data Types IV

- In other words, we can prove algebraic properties of SPARK operators after establishing correctness of abstract data types.
- This looks good on paper.
- But it is an overkill.
  - We only want to show algebraic properties, not correct data type implementations.
- What about arbitrary user-defined SPARK operators?
  - Representation functions can be obscure.

Interpretations of Algebraic Properties Revisited I

- To find a simpler solution, let us take another look at algebraic properties.
- Let `U` be an implementation of the set-theoretic union $\cup$.
- Since the concrete structure of `A U B` is different from those of `B U A`, we have

$$\texttt{A U B} \neq \texttt{B U A}.$$

- We interpret the equality $=$ too narrowly.

Interpretations of Algebraic Properties Revisited II

- Define the binary relation $\approx$ over concrete structures:

$$\approx \quad = \quad \{(\mathtt{S}, \mathtt{T}) : \ \mathtt{S} \text{ and } \mathtt{T} \text{ denote the same set.}\}$$

- Then we have for every `A` and `B`

$$\mathtt{A \ U \ B} \approx \mathtt{B \ U \ A}.$$

- This is the intended interpretation of algebraic properties.

Interpretations of Algebraic Properties Revisited III

- Our interpretation in fact coincides with Hoare's formulation.
- The binary relation $\approx$ can simply be

$$\approx \quad = \quad \{(\mathtt{S}, \mathtt{T}) : \mathcal{A}(\mathtt{S}) = \mathcal{A}(\mathtt{T})\}.$$

- Then

$$\text{for every } \mathtt{A} \text{ and } \mathtt{B} \quad \mathtt{A\ U\ B} \approx \mathtt{B\ U\ A}$$

  is a paraphrase of

$$\text{for every } \mathtt{A} \text{ and } \mathtt{B} \quad \mathcal{A}(\mathtt{A\ U\ B}) = \mathcal{A}(\mathtt{B\ U\ A}).$$

- This particular definition of $\approx$ is fine but unsatisfactory.
  - It needs the representation function $\mathcal{A}$.

Interpretations of Algebraic Properties Revisited IV

- Intended interpretations of algebraic properties depend on the interpretation of equality.
  - That is, the binary relation $\approx$.
- Two problems remain:
- What are the criteria for the soundness of $\approx$?
  - Taking $\approx$ to be the universal binary relation is not sound. Why?
- How to define such $\approx$ without representation functions?
  - Can it be computed automatically?

Interpretation by Bisimulation I

- Let us try to formulate $\approx$.
- What is a proper intended interpretation of equality?
- Intuitively, $\approx$ relates equivalent concrete structures.
- But how do we define "equivalence?"
- The process algebra community has solved this problem.
  - Thanks to Robin Milner.

Interpretation by Bisimulation II

- Informally, two processes are equivalent if no action can differentiate one from the other.
- In our context, we have

  two concrete structures are equivalent if no operation can differentiate one from the other.

- For instance, a good definition of $\approx$ must satisfy
  For every `A`, `A'`, `B`, `B'`

  $$\texttt{A} \approx \texttt{A'} \text{ and } \texttt{B} \approx \texttt{B'} \text{ imply } \texttt{A U B} \approx \texttt{A' U B'}$$

  among other operations of interests.

Interpretation by Bisimulation III

- Similar to bisimulation, $\approx$ is relative to operations.
  - If we only insert elements to sets, any two sets are "equal."
  - Insertion cannot differentiate one set from another.
- Depending on operations of interests, different definitions of $\approx$ are available.
  - Representation functions are no longer needed.
- $\approx$ does not verify correctness of data type implementations.
  - Just like bisimulation, it only relates equivalent concrete structures.
  - It is easier to check and not an overkill.

Higher-Order Operations and Logical Relations

- For SPARK, concrete structures often have higher-order operations.
  - Operations take functions as parameters.
- Our theory also covers such concrete structures.
- We borrow from logical relations in λ-calculus.

Verifying Algebraic Properties

- Algebraic properties can now be formally verified as follows.
  - Specify $\approx$.
  - Check if $\approx$ is a bisimulation (or logical relation).
  - Check algebraic properties by interpreting equality with $\approx$.
- No abstract objects are referred in this process.
- Verification can be done in automated software verification tools.
  - without proof assistants, that is.
- We have case studies in LEON.

Plan

Interested?

- There are more problems to be addressed in SPARK programming.
- I will briefly describe two (unsolved) problems.
  - Stability problem in numerical computation
  - SQL query optimization

Stability Problem I

- Recall that associative and commutative SPARK operators are required for transformations and actions.
- But floating-point operators do not have such algebraic properties.
- Particularly, floating-point addition is not associative.
  - Let `x` $=$ `1.0`, `y` $=$ `-1.0`, and `z` $=$ `1e-16`.
  - `1e-16` $=$ `(x + y) + z` $\neq$ `x + (y + z)` $=$ `0.0`
- No sound definition of $\approx$ can relate `1e-16` and `0.0`.
- Floating-point addition should not be used in SPARK transformations and actions.
  - But they are widely used!

Stability Problem II

- Non-deterministic outcomes can in fact be observed from a private function `AreaUnderCurve.of` in MLlib.
- Given an RDD of sample points of a curve, `AreaUnderCurve.of` performs the numerical integration by summing up areas of trapezoids defined by the curve.
- Let us consider the following integration

$$\int_{-2}^{2} x^{73} dx$$

- However `AreaUnderCurve.of` returns different answers in 50 runs on the same evenly distributed sample points on x^{73}.
- The outcomes are not deterministic.

Stability Problem III

- Non-deterministic outcomes are perhaps tolerable if they are not very different.
- With 8 worker nodes, we observe values from -8192.0 to 12288.0 in 50 runs.
- Recall the integration

$$\int_{-2}^{2} x^{73} dx = 0$$

  - since x^{73} is an odd function.
- Outcomes are (very) different from the mathematical result.

Stability Problem IV

- Unstable floating-point computation is always a problem in numerical methods.
- To have stable computation, a sequence of floating-point operations need to be performed in a certain order.
  - Mathematically equivalent sequences of such operations can have different stability.
- For SPARK, the problem is even more uncontrollable.
- Floating-point operations are not executed in any fixed-order due to concurrency.
- Is there a way to ensure stability in SPARK computation?

SQL Optimization I

- SPARK SQL provides an interface to write database queries.
- In SPARK, databases are modeled by RDDs.
- SQL queries are thus translated to SPARK transformations and actions.
- SPARK SQL goes even further to optimize the translation.

SQL Optimization II

- More than 30 local optimizations.
  - Data flow analysis, static evaluation, etc.
- Divided into 11 batched optimizations.
  - batched optimizations are iteratively performed.
- Correctness?
  - stability, algebraic properties of user-defined queries?
- Performance?
  - a performance model for SPARK?

Conclusions

- SPARK is now a popular and simple programming model for distributed computing.
- Unlike classical distributed computing, concurrency is restricted in SPARK computation.
- We have shown an abstract functional model and a proof technique for SPARK programs.
- We believe there are many opportunities for the verification community to offer.