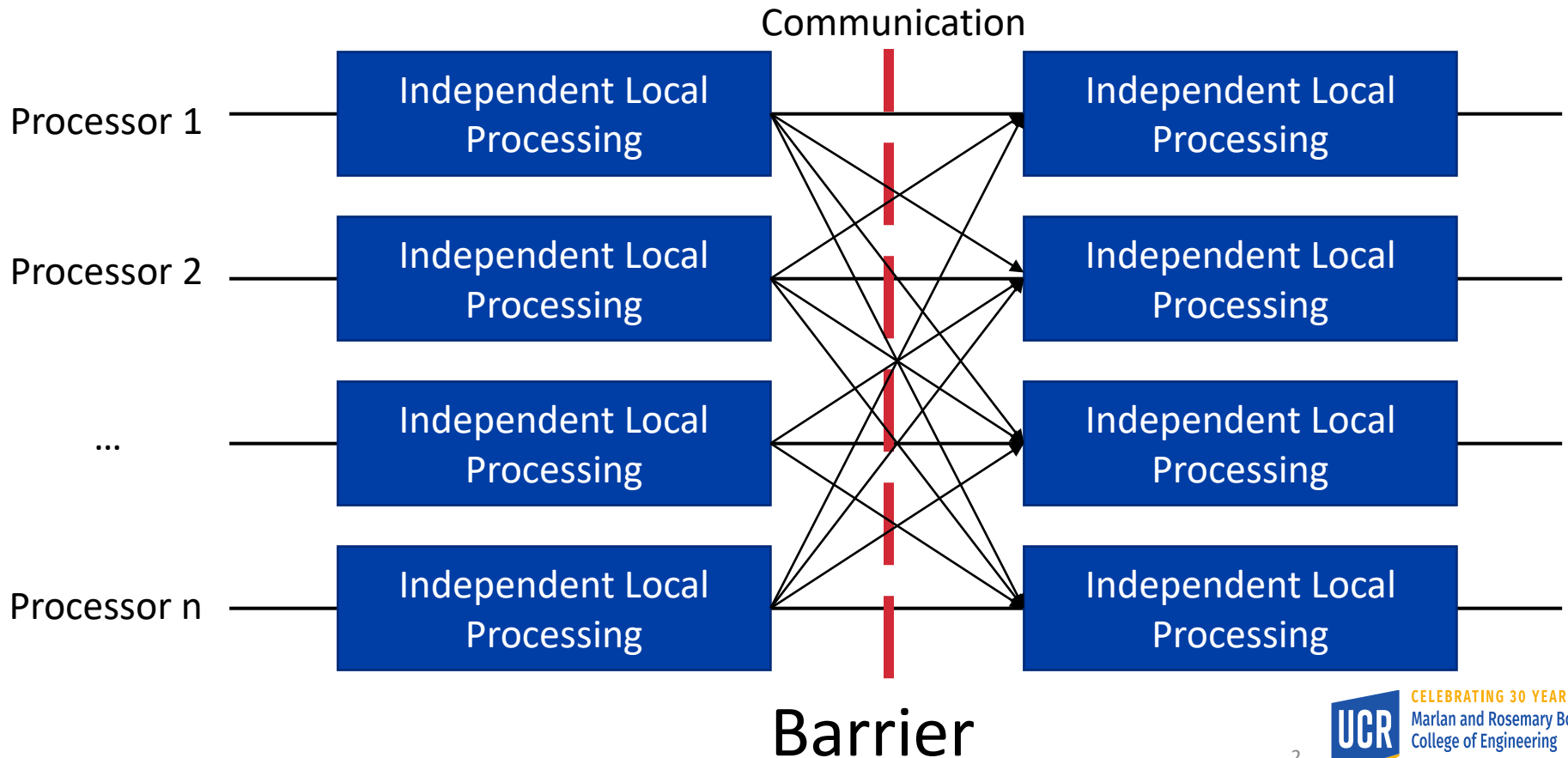


# Spark RDD Operations

Transformations and Actions

# RDD Processing Model

- RDD can be modeled using the Bulk Synchronous Parallel (BSP) model



# RDD ↔ BSP

- In Spark RDD, you can generally think of these two rules
  - Narrow dependency → Local processing
  - Wide dependency → Network communication

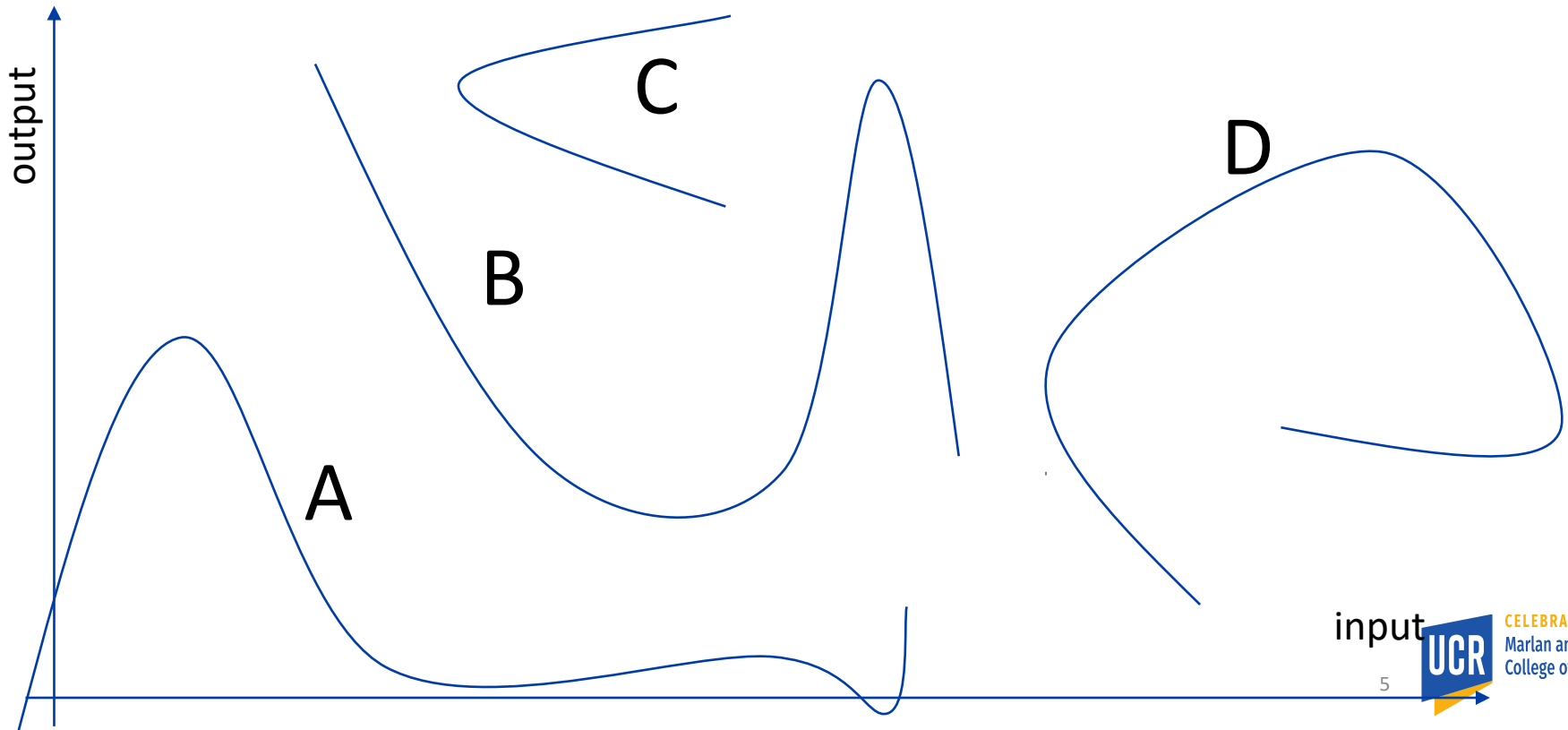
# Local Processing in RDD



- A simple abstraction for local processing
- Based on functional programming
- Local Processing(input: Iterator<T>, output: Writer<U>) {  
... // output.write(U)  
}

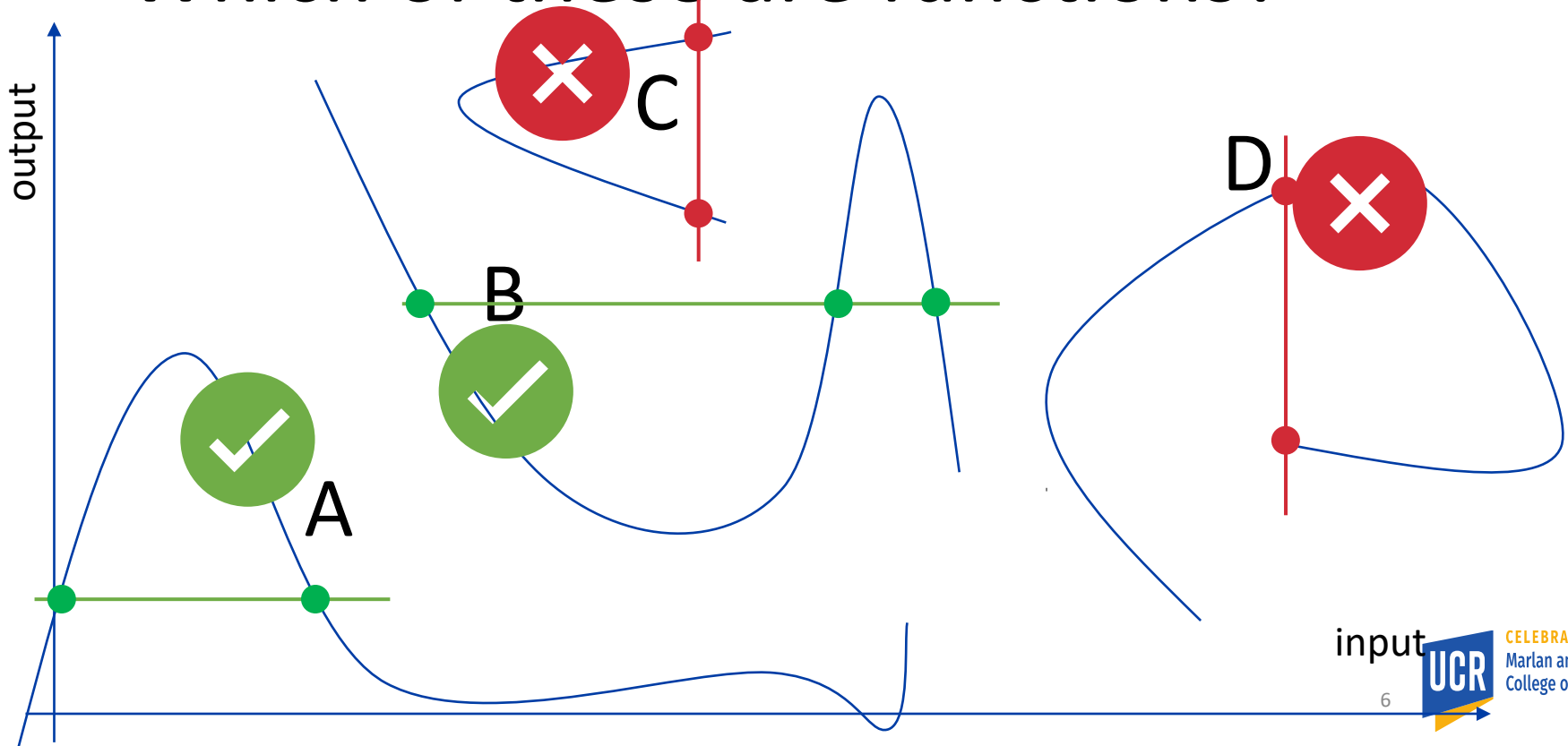
# Functional Programming

- RDD is a functional programming paradigm
- Which of these are functions?



# Functional Programming

- RDD is a functional programming paradigm
- Which of these are functions?



# Function Limitations

- For one input, the function should return one output
- The function should be memoryless
  - Should not remember past input
- The function should be stateless
  - Should not change any state when called
- It is up to the developer to enforce these properties

# Examples

```
Function1(x) {  
    return x + 5;  
}
```

```
Int sum  
Function2(x) {  
    sum += x;  
    return sum;  
}
```

```
RNG random;  
Function3(x) {  
    random.nextInt(0, x);  
}
```

```
Map<String, Int> lookuptable;  
Function4(x) {  
    return lookuptable.get(x);  
}
```

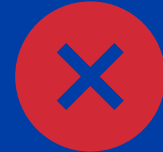


# Examples

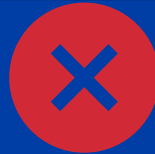
```
Function1(x) {  
    return x + 5;  
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Int sum  
Function2(x) {  
    sum += x;  
    return sum;  
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```



```
Map<String, Int> lookuptable;  
Function4(x) {  
    return lookuptable.get(x);  
}
```



# Network Communication

- a.k.a. shuffle operation
- Given a record  $r$  and  $n$  partitions:
  - Assign the record to one of the partitions  $[0, n - 1]$

# RDD Operations

- Spark is rich with operations
- Sometimes, you can do the same logic with more than one way
- In the following part, we will explain how different RDD operations work
- The goal is to understand the performance implications of these operations and choose the most efficient one

# RDD<T>#filter

- Filter is a function  $\{T \rightarrow \text{Boolean}\}$
- Applies the predicate function on each record and produces that tuple only if the predicate returns true
- Result RDD<T> with same or fewer records than the input
- Local Processing {  
  for-each (t in input) {  
    if (func(t))  
      output.write(t)  
  }  
}

# RDD<T>#map(func)

- $\text{func}: T \rightarrow U$
- Applies the map function to each record in the input to produce one record
- Results in RDD<U> with the same number of records as the input
- Local Processing {  
    for-each (t in input)  
        output.write(func(t))  
}

# RDD<T>#flatMap(func)

- func: T → Iterator<V>
- Applies the map function to each record and add all resulting values to the output RDD
- Result: RDD<V>
- This is the closest function to the Hadoop map function
- Local Processing {  
    Iterator<V> results = func(input);  
    for (V result : results)  
        output.write(result)  
}

# RDD<T>#mapPartition(func)

- func: Iterator<T>  $\rightarrow$  Iterator<U>
- Applies the map function to a list of records in one partition in the input and adds all resulting values to the output RDD
- Can be helpful in two situations
  - If there is a costly initialization step in the function
  - If many records can result in one record
- Result: RDD<U>

# RDD<T>#mapPartition(func)

- Local Processing {  
    results = func(input)  
    for-each (v in results)  
        output.write(v);  
}



## RDD<T>#mapPartitionWithIndex(func)

- func: (Integer, Iterator<T>) → Iterator<U>
- Similar to mapPartition but provides a unique index for each partition
- To achieve this in Spark, the partition ID is passed to the function

# RDD<T>#sample(r, f, s)

- r: Boolean: With replacement (true/false)
- f: Float: Fraction [0,1]
- s: Long: Seed for random number generation
- Returns RDD<T> with a sample of the records in the input RDD
- Can be implemented using `mapPartitionWithIndex` as follows
  - Initialize the random number generator based on seed and partition index
  - Select a subset of records as desired
  - Return the sampled records

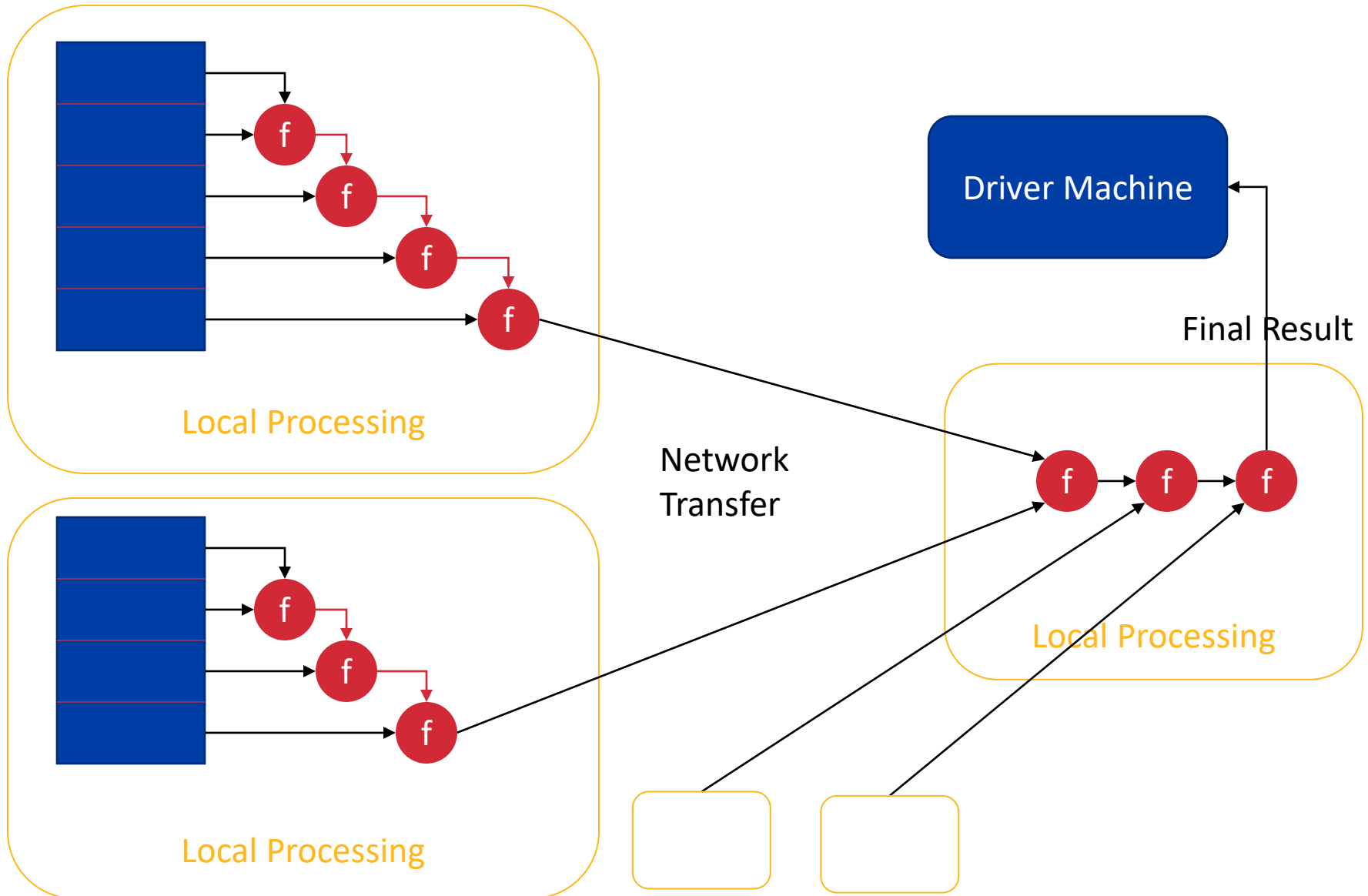
# RDD<T>#reduce(func)

- $\text{func}: (T, T) \rightarrow T$
- Reduces all the records to a single value by repeatedly applying the given function
- The function should be associative and commutative
- Result: T
- This is an action

# RDD<T>#reduce(func)

- mapPartition {  
    T result = input.next  
    for-each (r in input)  
        result = reduce(result, r)  
    return result  
}
- Shuffle: assign all records to one partition
- Collect partial results and apply the same function again

# RDD<T>#reduce(func)



# RDD<K,V>#reduceByKey(func)

- func:  $(V, V) \rightarrow V$
- Similar to reduce but applies the given function to each group separately
- Since there could be so many groups, this operation is a transformation that can be followed by further transformations and actions
- Result: RDD<K,V>
- By default, number of reducers is equal to number of input partitions but can be overridden

# RDD<K,V>#reduceByKey(func)

- mapPartition {  
  Map<K,V> results;  
  for-each ((k,v) in input) {  
    if (results.contains(k))  
      results[k] = reduce(results[k], v);  
    else  
      results[k] = v;  
  }  
}
- Shuffle by key, assign (k,v) to hash(k) **mod** n
- mapPartition {  
  // All input records have the same key  
  V result = value.next  
  for-each (v in values)  
    result = reduce(result, v)  
  output.write(k, v)  
}

# RDD<T>#distinct()

- Removes duplicate values in the input RDD
- Returns RDD<T>
- Implemented as follows  
map(x => (x, null)).  
reduceByKey((x, y) => x,  
numPartitions).  
map(\_.\_1)



# Limitation of reduce methods

- Both reduce methods have a limitation is that they have to return a value of the same type as the input.
- Let us say we want to implement a program that operates on an `RDD<Integer>` and returns one of the following values
  - 0: Input is empty
  - 1: Input contains only odd values
  - 2: Input contains only even values
  - 3: Input contains a mix of even and odd values

## RDD<T>#aggregate(zero, seqOp, combOp)

- zero: U - Zero value of type U
  - seqOp: (U, T)  $\rightarrow$  U – Combines the aggregate value with an input value
  - combOp: (U, U)  $\rightarrow$  U – Combines two aggregate values
  - Like reduce, aggregate is an action
  - Returns U
- 
- Similarly, aggregateByKey is a transformation that takes RDD<K,V> and returns RDD<K,U>

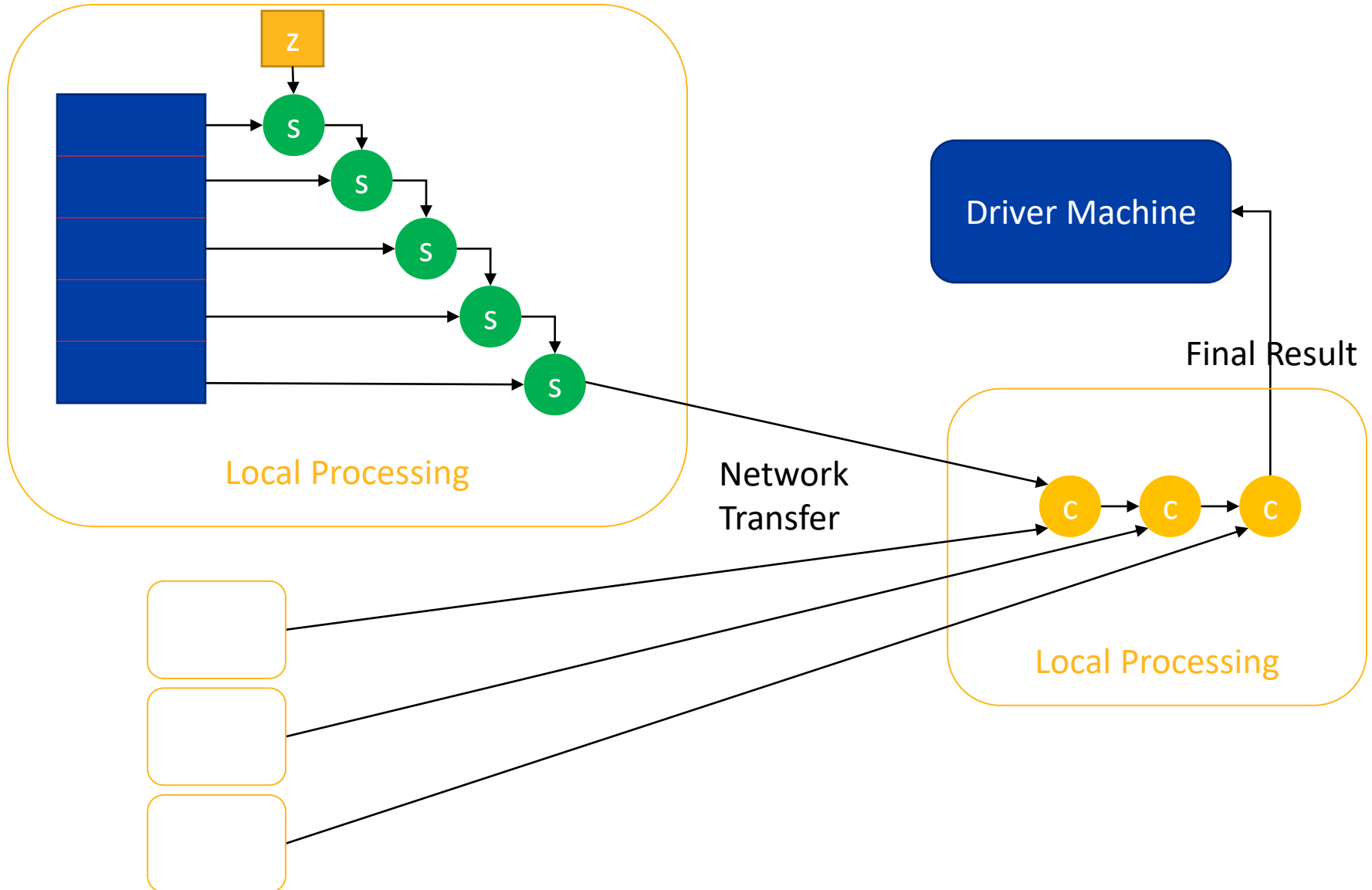
## RDD<T>#aggregate(zero, seqOp, combOp)

- mapPartition {  
    U partialResult = zero  
    for-each (t in input)  
        result = seqOp(partialResult, t)  
    return partialResult  
}
- Collect all partial results into one partition
- mapPartition {  
    U finalResult = input.next  
    for-each (u in input)  
        finalResult = combOp(finalResult, u)  
    return finalResult  
}

## RDD<T>#aggregate(zero, seqOp, combOp)

- Example:
- RDD<Integer> values
- Byte marker = values.aggregate( (Byte)0, (result: Byte, x: Integer) => {  
    if (x % 2 == 0) // Even  
        return result | 2;  
    else  
        return result | 1;  
}, (result1: Byte, result2: Byte) => result1 | result2);

# RDD<T>#aggregate(zero, seqOp, combOp)



# RDD<K,V>#groupByKey()

- Groups all values with the same key into the same partition
- Closest to the shuffle operation in Hadoop
- Returns RDD<K, Iterator<V>>
- Performance notice: By default, all values are kept in memory so this method can be very memory consuming.
- Unlike the reduce and aggregate methods, this method does not run a combiner step, i.e., all records get shuffled over network

# Further Readings

- List of common transformations and actions
  - <http://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations>
- Spark RDD Scala API
  - <http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.rdd.RDD>