

SPARK STREAMING

Say you work for a
payment service



Say you work for a
payment service



Google wallet



The number of
failed payments/
second

is a mission
critical metric



The number
failed payments/second

Typically business
reports are
published at a
certain frequency

Quarterly,
Monthly,
Weekly,
Daily,
Hourly



The number of
failed payments/second

Quarterly,
Monthly,
Weekly,
Daily,
Hourly

These reports require
batch processing



The number of
failed payments/second

Quarterly,
Monthly,
Weekly,
Daily,
Hourly

batch processing
**Data is collected
and stored in a
database / HDFS**



The number of
failed payments/second



Quarterly,
Monthly,
Weekly,
Daily,
Hourly

batch processing
Processing tasks
are run at the
required frequency

The number of
failed payments/second



Quarterly,
Monthly,
Weekly,
Daily,
Hourly

batch processing
Each processing
task runs on a
'batch' of data

To monitor



The number of
failed payments/second

batch processing
simply isn't enough!

The number of
failed payments/second



If this metric
shows a spike

You need to know
immediately

The number
failed payments/second



You need to react
within seconds or
minutes

The number of
failed payments/second

Otherwise, it could mean very
bad things

Loss of reputation, customer
trust, revenue

Being slow to react could be a
death blow to your business!



The number of
failed payments/second



Mission critical metrics

need to be monitored

in Real Time

The number of
failed payments/second

Real Time

Payment logs are created
by your payment service

These logs need to be
processed as they are
created



The number of
failed payments/second

Real Time

Payment logs are created
by your payment service

These logs need to
be processed **as**
they are created



Streaming data

Stream Processing

The number of
failed payments/second



Stream Processing

Typically, distributed
computing systems like
MapReduce and even Spark

Process data from stable
storage (database, HDFS)

The number of
failed payments/second



Stream Processing

Since they read data
from disk

There would be **too much lag** in
the processing of Streaming data

The number of
failed payments/second



Stream Processing

Usually, folks end up
using separate systems

For batch processing
and stream processing

The number of
failed payments/second



Stream Processing

Apache Storm for
example

is a standalone Stream
processing application

The number of
failed payments/second



Stream Processing

Spark is envisioned as a
general purpose engine to solve
all data processing problems

The number of
failed payments/second



Stream Processing

**Spark Streaming provides
Stream processing
capability within Spark**

The number of
failed payments/second



Stream Processing

Spark Streaming means that
you can use a single engine
(Spark) for both batch and
stream processing

Spark
Streaming

Just like typical **Spark**
applications involve
the use of **RDDs**

Spark Streaming applications
involve the use of

DStreams

DStreams

Spark
Streaming

Let's say you have a stream of payment logs

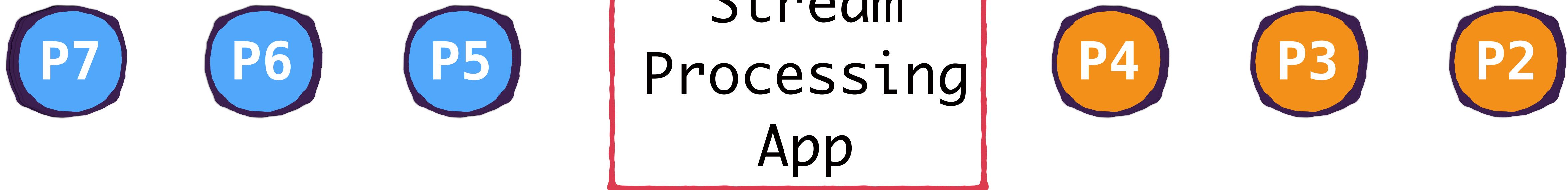


Typically, a stream processing application will process each individual log

DStreams

Spark
Streaming

Stream processing typically



DStreams

Spark
Streaming



In a Spark Streaming app,
the entire stream of logs is
represented as a **DStream**

DStreams

Spark
Streaming



The DStream has a property called
batch interval (measured in seconds)

DStreams

Spark
Streaming

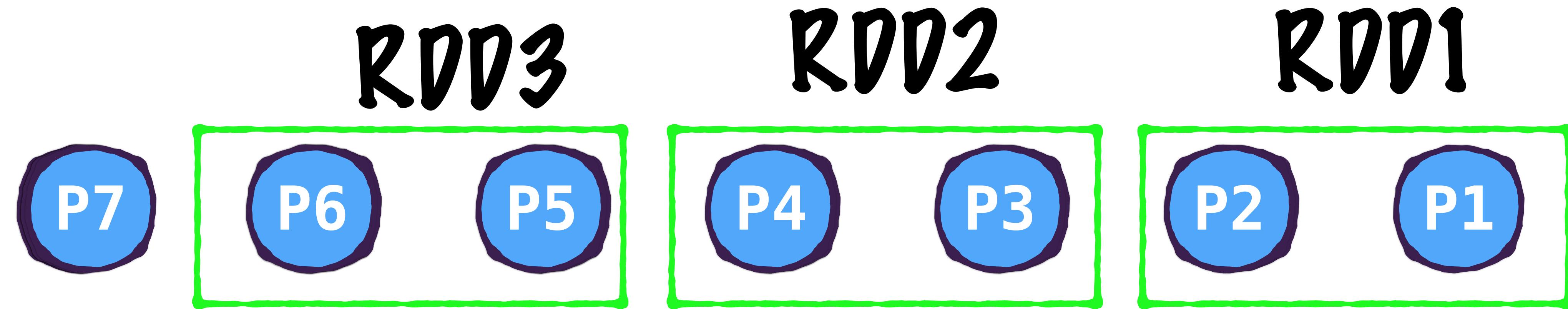


batch interval

All data arriving within this interval is grouped into an RDD

DStreams

Spark
Streaming



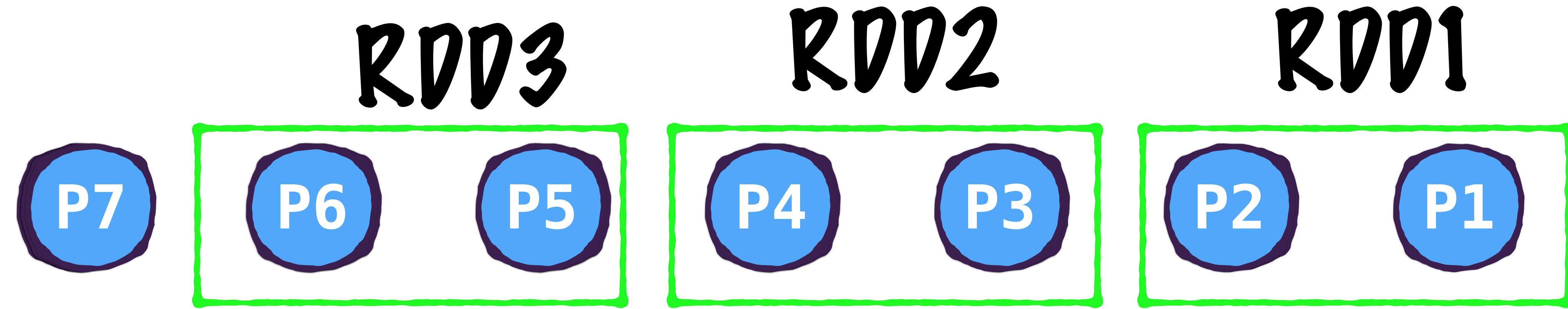
batch interval

Let's say the batch interval is 1 sec

The stream consists of 2 logs per second

DStreams

Spark
Streaming

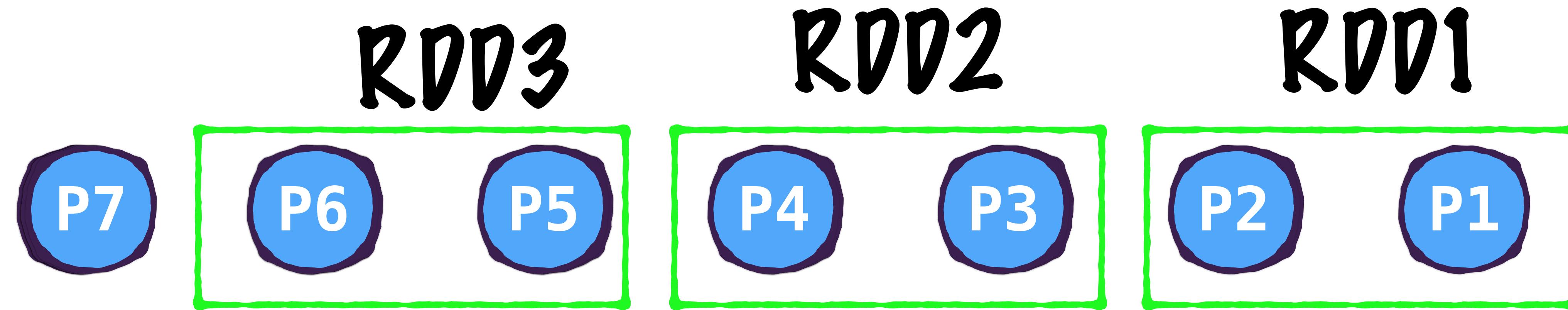


The DStream is a
sequence of RDDs

1 RDD every batch
interval

DStreams

Spark
Streaming

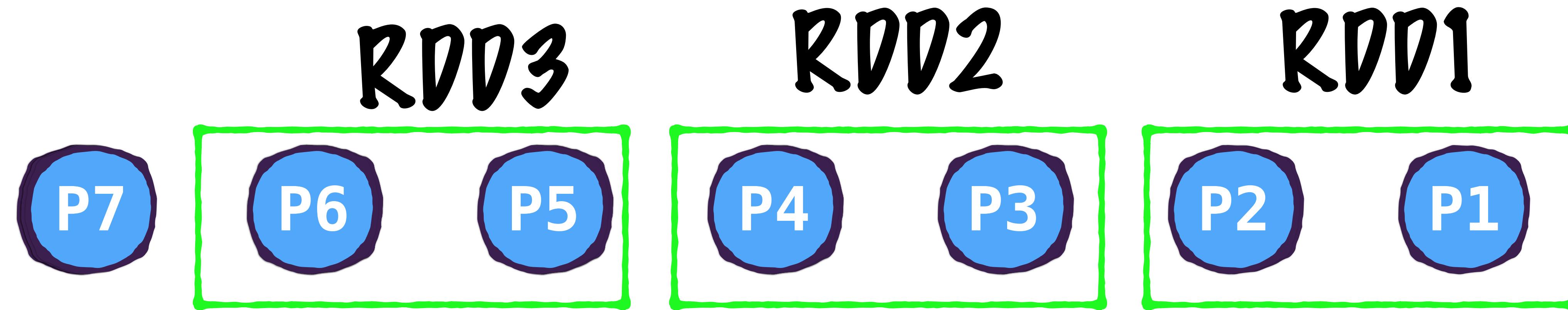


You can apply
transformations
and actions on
DStreams

They will be applied
to each of these
RDDs as they are
created

DStreams

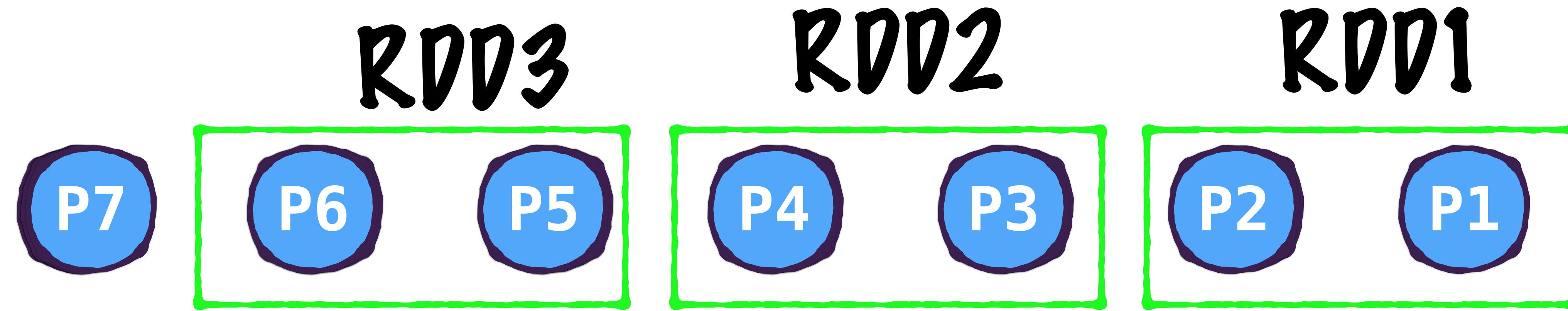
Spark
Streaming



With DStreams, Spark
still does **batch processing**

DStreams

Spark
Streaming



With DStreams, Spark
still does batch processing

On individual RDDs in this stream

DStreams

Spark
Streaming

Let's look at some code for a
Spark Streaming application

DStreams

The objective:

Monitor all text data
that arrives at a
certain port

Spark
Streaming

DStreams

The objective:

Monitor all text data that arrives at a certain port

Filter any lines that contain the word “ERROR”

Spark
Streaming

DStreams

The objective:

Listen to all text data that arrives at a certain port

Filter any lines that contain the word “ERROR”

Print a count to screen

Spark
Streaming

Spark Streaming

```
import sys

from pyspark import SparkContext
from pyspark.streaming import StreamingContext

if __name__ == "__main__":
    sc = SparkContext(appName="StreamingErrorCount")
    ssc = StreamingContext(sc, 1)

    ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
    lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
    counts = lines.flatMap(lambda line: line.split(" "))\
        .filter(lambda word:"ERROR" in word)\n        .map(lambda word: (word, 1))\
        .reduceByKey(lambda a, b: a+b)

    counts.pprint()
    ssc.start()
    ssc.awaitTermination()
```

```
import sys
```

```
from pyspark import SparkContext
from pyspark.streaming import StreamingContext
```

```
if __name__ == "__main__":
```

We'll need to set up the
SparkContext and a
StreamingContext

```
sc = SparkContext(appName="StreamingErrorCo
ssc = StreamingContext(sc, batchInterval)
ssc.checkpoint("hdfs://user/swethakola/apud")
lines = ssc.socketTextStream(sys.argv[1], i
```

```
import sys
```

```
from pyspark import SparkContext
from pyspark.streaming import StreamingContext
```

```
if __name__ == "__main__":
```

A StreamingContext is
used to create DStreams

```
sc = SparkContext("local[2]", "WordCount")
ssc = StreamingContext(sc, 1)
ssc.checkpoint("hdfs://user/swethakolalapudra@ip-172-31-10-104:9000/wordcount")
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

```
import sys
```

```
from pyspark import SparkContext
from pyspark.streaming import StreamingContext
```

```
if __name__ == "__main__":
```

Import SparkContext
and StreamingContext

```
sc = SparkContext(appName="PythonWordCount", master="local[4]")
ssc = StreamingContext(sc, 1)
lines = ssc.socketTextStream(sys.argv[1], 9999)
```

```
__name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, 1)
```

Set up the
SparkContext and
StreamingContext

```
__name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, 1)
```

The StreamingContext
is where you set the
batch interval

```
__name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, [1])
```

The batch interval
is set to 1 second

```
__name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, [1])
```

ssc.checkPoint("hdfs://user/swethakolalapudi/stre
lines = ssc.socketTextStream(ssc.getSystemPropert
counts = lines.flatMap(lambda line: line.split(" "
"").filter(lambda word: word != "ERRORIN" and upper
"case(word) in errorWords).map(lambda word: (upper
"case(word), 1))
counts.reduceByKeyAndWindow(lambda old, new:
old + new, Duration(10000000000L), Duration(1000000000L))
counts.pprint()

This will be the batch interval
for all DStreams we create
using this StreamingContext

Spark Streaming

```
f __name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, 1)
```

```
ssc.checkpoint("hdfs://user/swethakolalapudi/streaming")
```

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
counts = lines.flatMap(lambda line: line.split(" ")).map(lambda word: (word, 1)).reduceByKey(lambda a, b: a + b)
counts.pprint()
ssc.start()
ssc.awaitTermination()
```

This is some additional setup we need for fault-tolerance

Spark Streaming

```
f __name__ == "__main__":
```

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, 1)
```

```
ssc.checkpoint("hdfs://user/swethakolalapudi/streaming")
```

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
counts = lines.flatMap(lambda line: line.split(" "))\
    .filter(lambda line: line != "")\
    .map(lambda word: (word, 1))\
    .reduceByKey(lambda a, b: a + b)
counts.pprint()
ssc.start()
ssc.awaitTermination()
```

**It sets a specified location
where a backup of the data is
saved at a certain frequency**

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

Create the DStream

Spark Streaming

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

A DStream that reads text data
which arrives at a specified port

Spark Streaming

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

The hostname where the data
will arrive

Spark Streaming

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

The port where the data arrives

Spark Streaming

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

Both these arguments will be passed at the commandline when we submit this script

Spark Streaming

```
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
```

```
> spark-submit Streaming.py localhost 9999
```

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

Apply any transformations
and actions on the DStream

This looks as if the operations
are applied on the entire DStream

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

Internally, the operations are applied
to each individual RDD in the DStream

flatMap converts an RDD with lines into an RDD with words

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

Filter for words that have
the substring “ERROR”

Each word is mapped to **(word, 1)**

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

Returns (word, count)

Prints the count to screen

```
counts.print()
```

This method is called for each individual RDD in the DStream

```
counts.pprint()
```

Since batch interval = 1 s, an RDD is created every second

```
counts.pprint()
```

Finally, we have to actually tell
the StreamingContext to start
listening for Streaming Data

```
ssc.start()  
ssc.awaitTermination()
```

Spark Streaming

```
import sys

from pyspark import SparkContext
from pyspark.streaming import StreamingContext

if __name__ == "__main__":

    sc = SparkContext(appName="StreamingErrorCount")
    ssc = StreamingContext(sc, 1)

    ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
    lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
    counts = lines.flatMap(lambda line: line.split(" "))\
        .filter(lambda word:"ERROR" in word)\n        .map(lambda word: (word, 1))\
        .reduceByKey(lambda a, b: a+b)

    counts.pprint()
    ssc.start()
    ssc.awaitTermination()
```

Streaming.py

```
import sys

from pyspark import SparkContext
from pyspark.streaming import StreamingContext

if __name__ == "__main__":
    sc = SparkContext(appName="StreamingErrorCount")
    ssc = StreamingContext(sc, 1)

    ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
    lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
    counts = lines.flatMap(lambda line: line.split(" "))\
        .filter(lambda word: "ERROR" in word)\n        .map(lambda word: (word, 1))\n        .reduceByKey(lambda a, b: a+b)

    counts.pprint()
    ssc.start()
    ssc.awaitTermination()
```

Spark
Streaming

To run this code, first start a stream at your localhost using the netcat utility

> nc -lk 9999

Streaming.py

```
import sys

from pyspark import SparkContext
from pyspark.streaming import StreamingContext

if __name__ == "__main__":
    sc = SparkContext(appName="StreamingErrorCount")
    ssc = StreamingContext(sc, 1)

    ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
    lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
    counts = lines.flatMap(lambda line: line.split(" "))\
        .filter(lambda word: "ERROR" in word)\n        .map(lambda word: (word, 1))\n        .reduceByKey(lambda a, b: a+b)

    counts.pprint()
    ssc.start()
    ssc.awaitTermination()
```

Spark
Streaming

> nc -lk 9999

In a separate terminal
submit your script

> spark-submit Streaming.py localhost 9999

Streaming.py

Spark
Streaming

```
> spark-submit Streaming.py localhost 9999
```

Spark will start
listening for the
streaming data at
the 9999 port

```
> nc -lk 9999
```

Streaming.py

Spark
Streaming

> spark-submit Streaming.py localhost 9999

```
Time: 2016-06-24 01:27:15
```

```
Time: 2016-06-24 01:27:16
```

```
Time: 2016-06-24 01:27:17
```

> nc -lk 9999

The batch interval
is 1 second

Streaming.py

```
> spark-submit Streaming.py localhost 9999
```

```
Time: 2016-06-24 01:27:15
```

```
Time: 2016-06-24 01:27:16
```

```
Time: 2016-06-24 01:27:17
```

```
> nc -lk 9999
```

Anything typed
here will be
processed by
Spark

Spark
Streaming

Streaming.py

> spark-submit Streaming.py localhost 9999

```
-----  
Time: 2016-06-24 01:27:15  
-----
```

```
Time: 2016-06-24 01:27:16  
-----
```

```
Time: 2016-06-24 01:27:17  
-----
```

```
Time: 2016-06-24 01:37:00  
-----
```

```
Time: 2016-06-24 01:37:01  
-----
```

```
(u'ERROR', 1)
```

Spark
Streaming

> nc -lk 9999

This line won't be printed

This line has ERROR

Streaming.py

Spark
Streaming

> spark-submit Streaming.py localhost 9999

```
-----  
Time: 2016-06-24 01:37:00  
-----
```

```
Time: 2016-06-24 01:37:01  
-----
```

```
(u'ERROR', 1)  
-----
```

```
Time: 2016-06-24 01:37:06  
-----
```

```
(u'ERROR', 1)
```

> nc -lk 9999

This line won't be printed

This line has ERROR

This line has ERROR too

We typed each
sentence after a
couple of seconds

Streaming.py

Spark
Streaming

> spark-submit Streaming.py localhost 9999

```
-----  
Time: 2016-06-24 01:37:00  
-----
```

```
Time: 2016-06-24 01:37:01  
-----
```

```
(u'ERROR', 1)  
-----
```

```
Time: 2016-06-24 01:37:06  
-----
```

```
(u'ERROR', 1)
```

> nc -lk 9999

This line won't be printed

This line has ERROR

This line has ERROR too

Each line
went into a
separate RDD

Streaming.py

Spark
Streaming

> spark-submit Streaming.py localhost 9999

```
-----  
Time: 2016-06-24 01:37:00  
-----
```

```
Time: 2016-06-24 01:37:01  
-----
```

```
(u'ERROR', 1)  
-----
```

```
Time: 2016-06-24 01:37:06  
-----
```

```
(u'ERROR', 1)
```

> nc -lk 9999

This line won't be printed

This line has ERROR

This line has ERROR too

Each line got
processed
individually

Streaming.py

```
> spark-submit Streaming.py localhost 9999
```

```
Time: 2016-06-24 01:37:00
```

```
Time: 2016-06-24 01:37:01
```

```
(u'ERROR', 1)
```

```
Time: 2016-06-24 01:37:06
```

```
(u'ERROR', 1)
```

The count is
from a single
RDD, not
accumulated
across RDDs

DStreams have 2 types of transformations

Stateless

Regular transformations
like map, reduceByKey etc

Stateful

reduceByWindow,
reduceByKeyAndWindow
etc

Stateless

Regular transformations
like map, reduceByKey etc

These transformations apply
on each individual RDD in the
DStream

These are used to accumulate
results across the RDDs in the
DStream

Stateful

reduceByWindow,
reduceByKeyAndWindow
etc

Stateful transformations
depend upon a Sliding Window

Stateful

reduceByWindow,
reduceByKeyAndWindow
etc

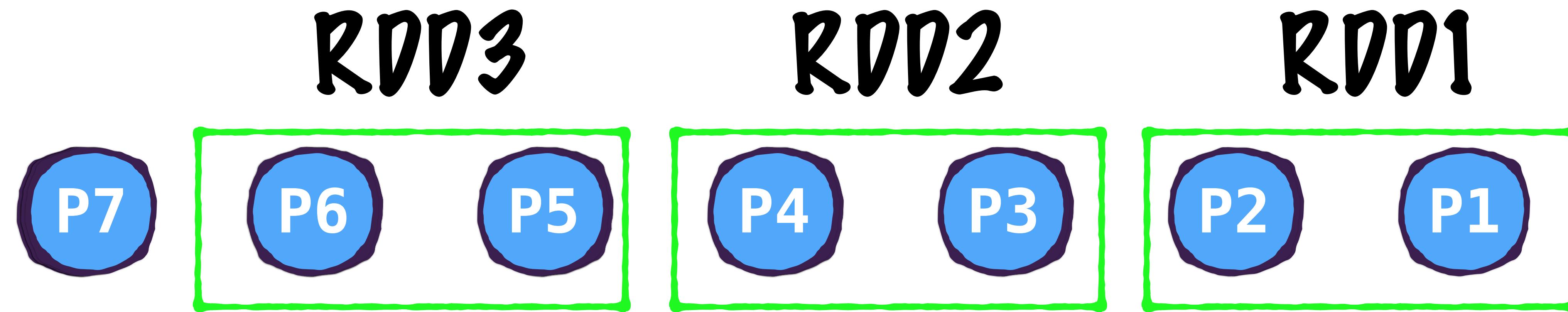
A Sliding Window consists of
multiple RDDs in the DStream

Stateful

reduceByWindow,
reduceByKeyAndWindow
etc

Sliding Window

Spark
Streaming

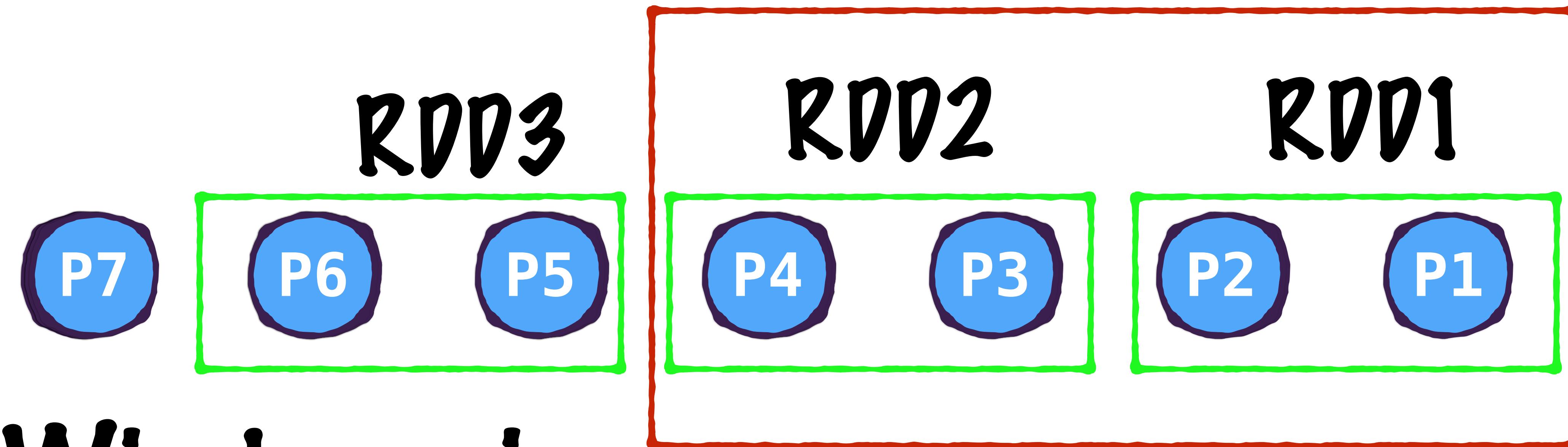


Let's say the batch
interval is 1 sec

The stream consists
of 2 logs per second

Sliding Window

Spark
Streaming

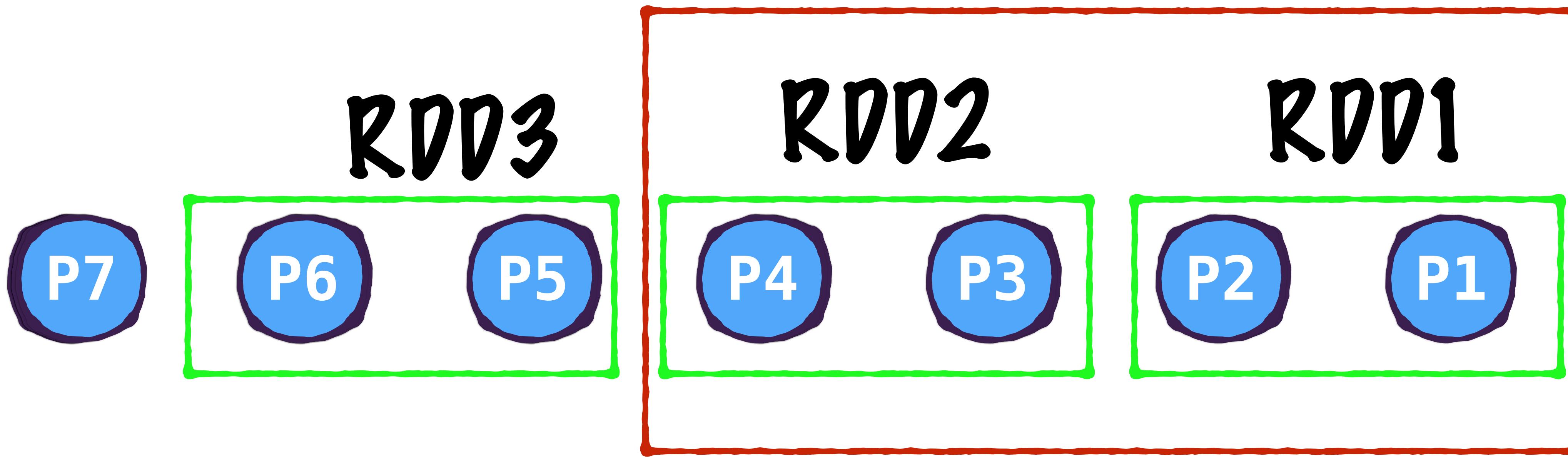


Window size
is 2 seconds

Sliding interval
is 1 second

Sliding Window

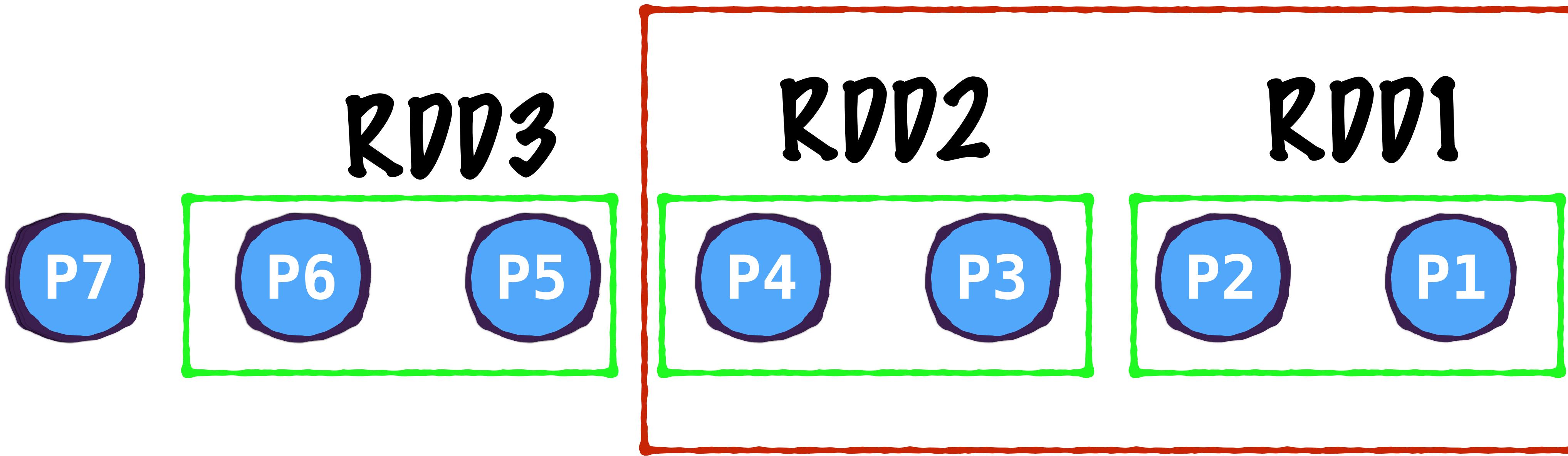
Spark
Streaming



Window at $t = 2s$

Sliding Window

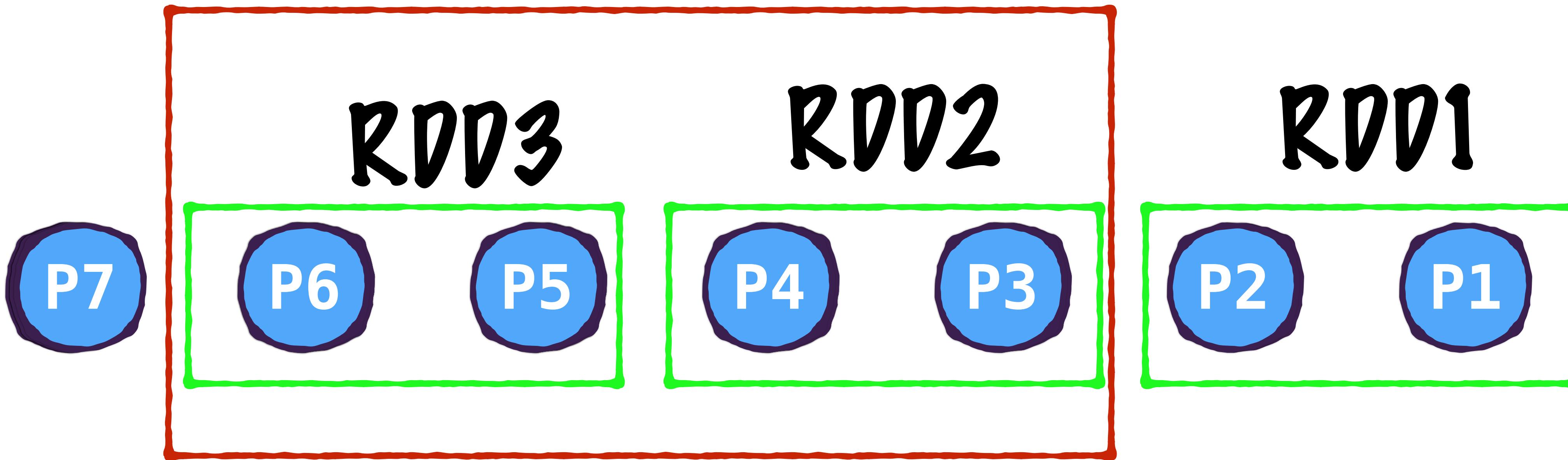
Spark
Streaming



A transformation on this window will treat both RDDs as a combined RDD

Sliding Window

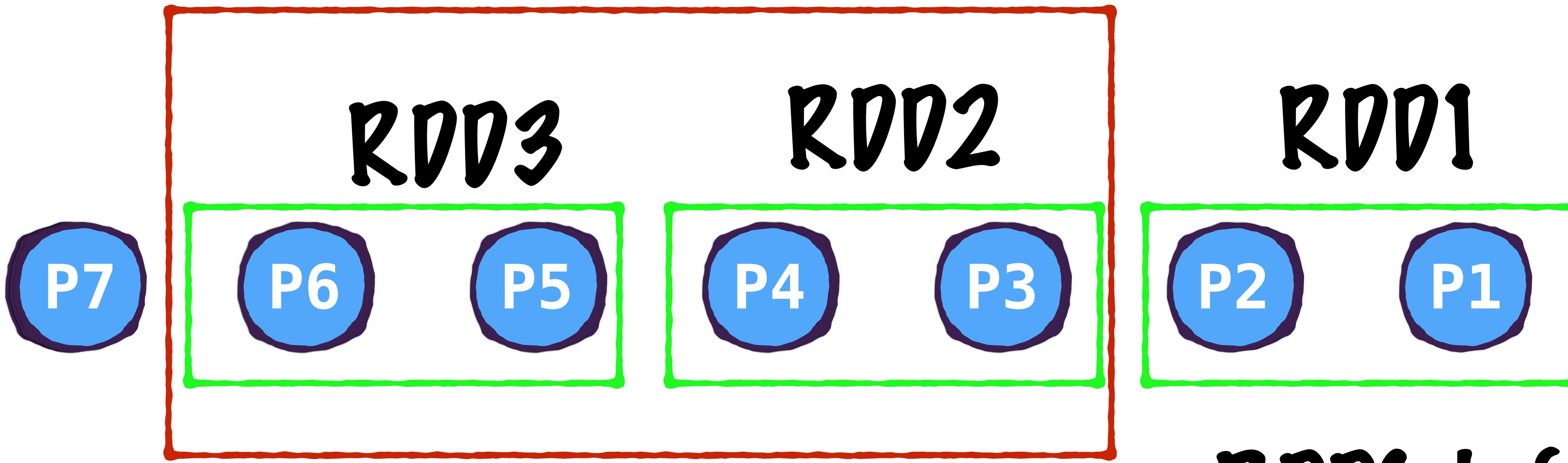
Spark
Streaming



Window at $t = 3s$

Sliding Window

Spark
Streaming

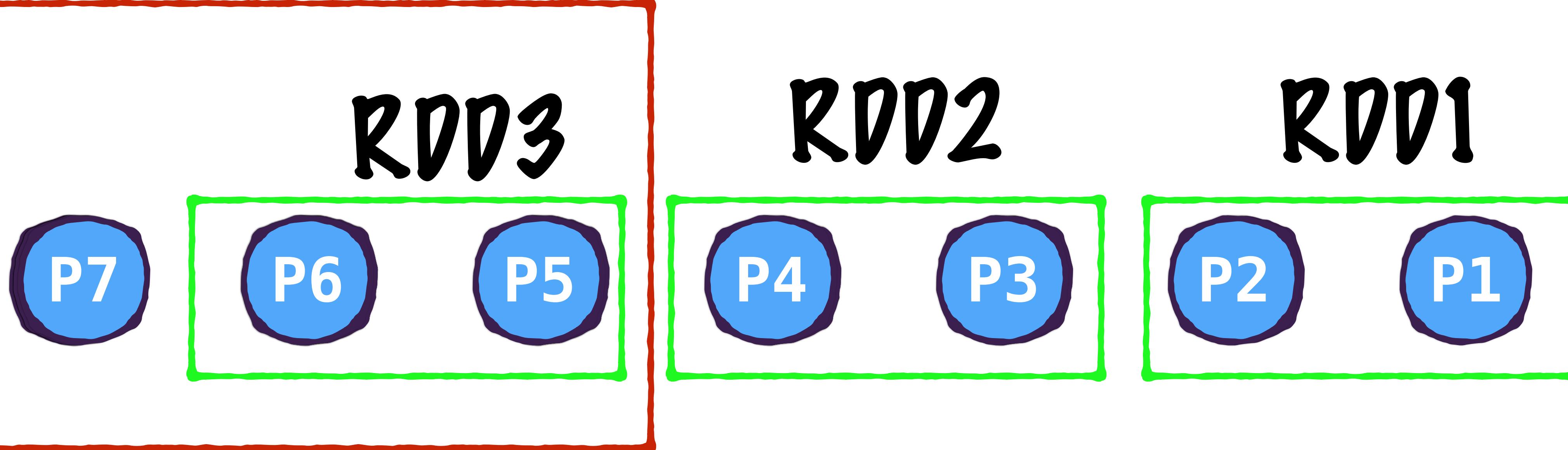


RDD3 entered the window

RDD1 left the window

Sliding Window

Spark
Streaming



Window at $t = 4s$

Here is our old code

```
import sys

from pyspark import SparkContext
from pyspark.streaming import StreamingContext

if __name__ == "__main__":

    sc = SparkContext(appName="StreamingErrorCount")
    ssc = StreamingContext(sc, 1)

    ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
    lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]))
    counts = lines.flatMap(lambda line: line.split(" "))\
        .filter(lambda word:"ERROR" in word)\n        .map(lambda word: (word, 1))\
        .reduceByKey(lambda a, b: a+b)

    counts.pprint()
    ssc.start()
    ssc.awaitTermination()
```

Let's update the code to add a stateful transformation

```
counts = lines.flatMap(lambda line: line.split(" "))\\
    .filter(lambda word:"ERROR" in word)\\
    .map(lambda word: (word, 1))\\
    .reduceByKey(lambda a, b: a+b)
```

```
counts.pprint()
ssc.start()
ssc.awaitTermination()
```

Spark Streaming

```
sc = SparkContext(appName="StreamingErrorCount")
ssc = StreamingContext(sc, 1)

ssc.checkpoint("hdfs:///user/swethakolalapudi/streaming")
lines = ssc.socketTextStream(sys.argv[1], int(sys.argv[2]), int(sys.argv[3]))
counts = lines.flatMap(lambda line: line.split(" "))\
    .filter(lambda line:"ERROR" in line)\n    .map(lambda word: (word, 1))\n    .reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, 30, 10)\n\n    .reduceByKey(lambda a, b: a+b)\n\ncounts.pprint()
ssc.start()
ssc.awaitTermination()
```

We changed `reduceByKey` to
`reduceByKeyAndWindow`

```
= lines.flatMap(lambda line: line.split(" "))\n    .filter(lambda line:"ERROR" in line)\n    .map(lambda word: (word, 1))\n    .reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y)
```

This part extracts words from the text and creates pairs (word,1)

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
map(lambda word: (word, 1))\\  
reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, 30, 10)
```

This will sum values with the
same key

(word,1)

(word,count)

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

The window size is 30 seconds

Sliding interval is 10 seconds

Batch interval is 1 second (set in
StreamingContext)

Spark Streaming

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

Window = 30 s

Slide = 10 s

Batch = 1s

A new RDD is created
every second

Spark Streaming

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

Window = 30 s

Slide = 10 s

Batch = 1s

A new RDD is created
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Spark Streaming

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

Window = 30 s

Slide = 10 s

Batch = 1s

A window consists
of 30 RDDs

Spark Streaming

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

Window = 30 s

Slide = 10 s

Batch = 1s

Every 10s, a new window is created

Spark Streaming

```
es.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, [30, 10])
```

Window = 30 s

Slide = 10 s

Batch = 1s

10 RDDs leave the window,
10 RDDs enter the window

10 RDDs leave the window,
10 RDDs enter the window

```
lines.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, 30, 10)
```

When RDDs enter the window,
add the values in the RDDs to the
word count

10 RDDs leave the window,
10 RDDs enter the window

```
lines.flatMap(lambda line: line.split(" "))\\  
.filter(lambda line:"ERROR" in line)\\  
.map(lambda word: (word, 1))\\  
.reduceByKeyAndWindow(lambda x, y: x + y, lambda x, y: x - y, 30, 10)
```

When RDDs leave the window,
subtract the values in the RDDs
from the word count

Sliding windows are
useful to observe trends

Visualizing such output in chart form
will allow us to see spikes, such as
when sudden payment errors occur!