

Real Time Recommendations using Spark Streaming

Elliot Chow

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Why?

- React more quickly to changes in interest
- Time-of-day effects
- Real-world events

Trending Now



New Releases

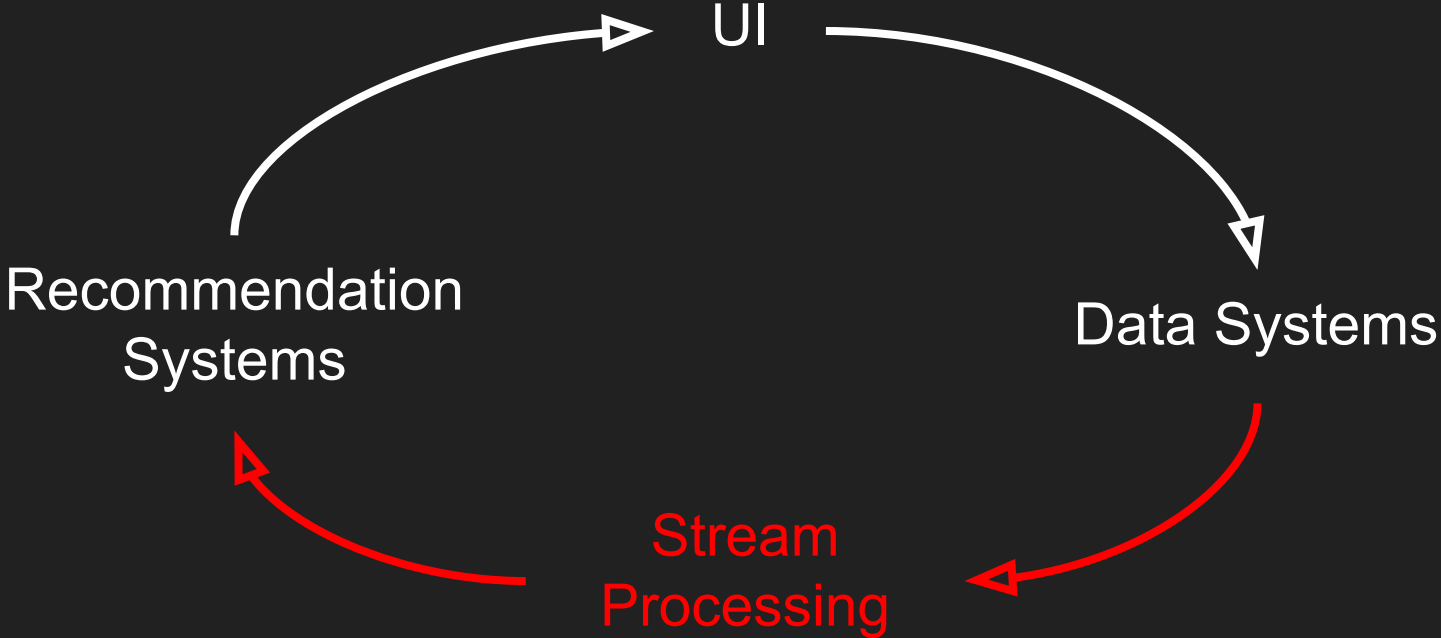


Because you watched The Get Down



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Feedback Loop

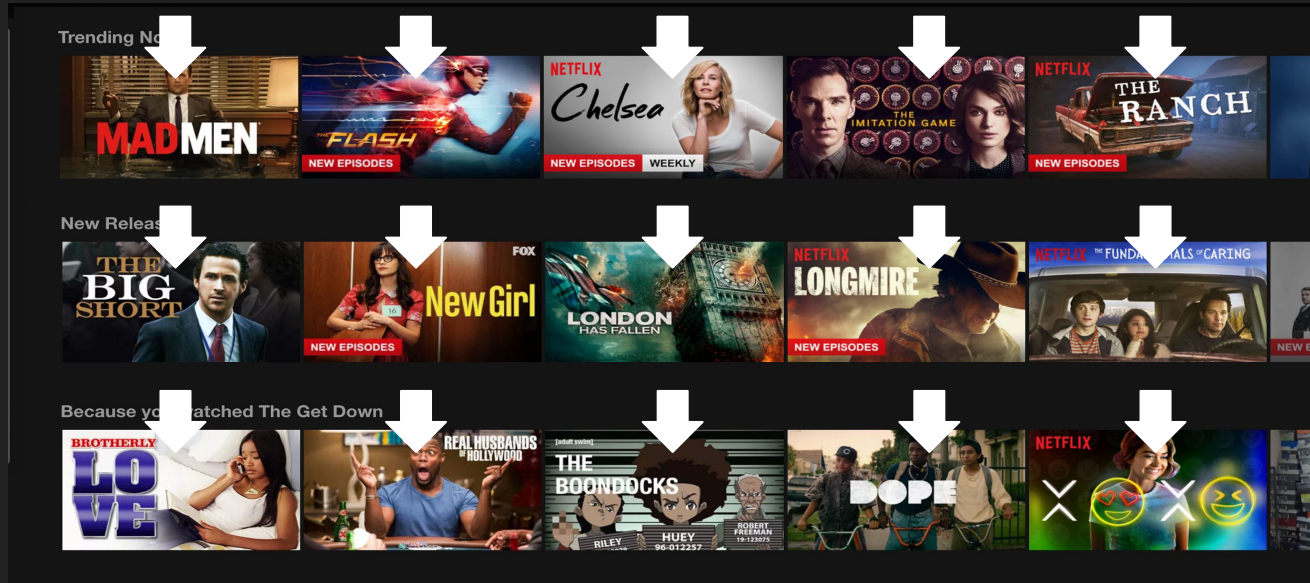


Trends Data

- What people browse: impressions
- What people watch: plays

Trends Data - Impressions

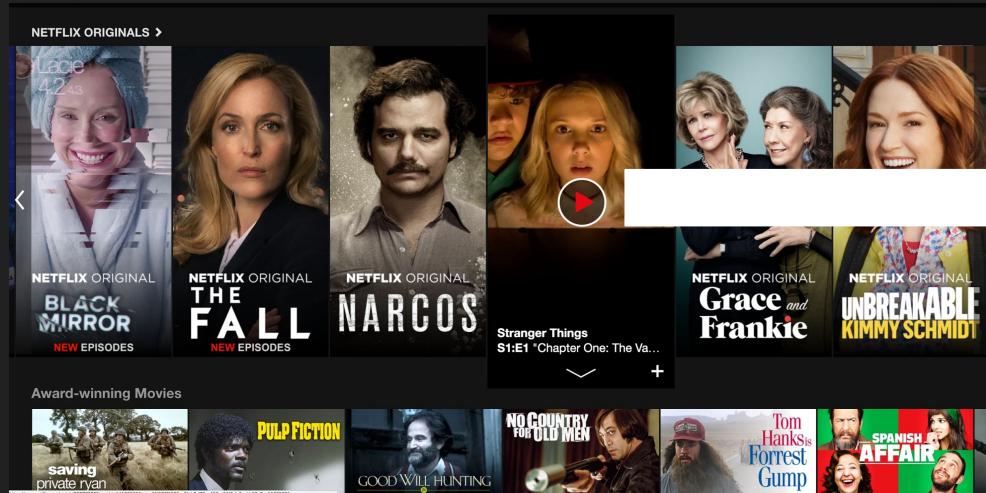
Appearance of a video in the viewport



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Trends Data - Plays

Member plays a video

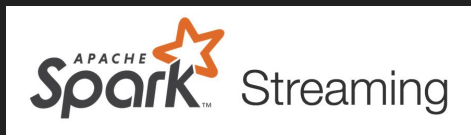


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Why Spark Streaming?

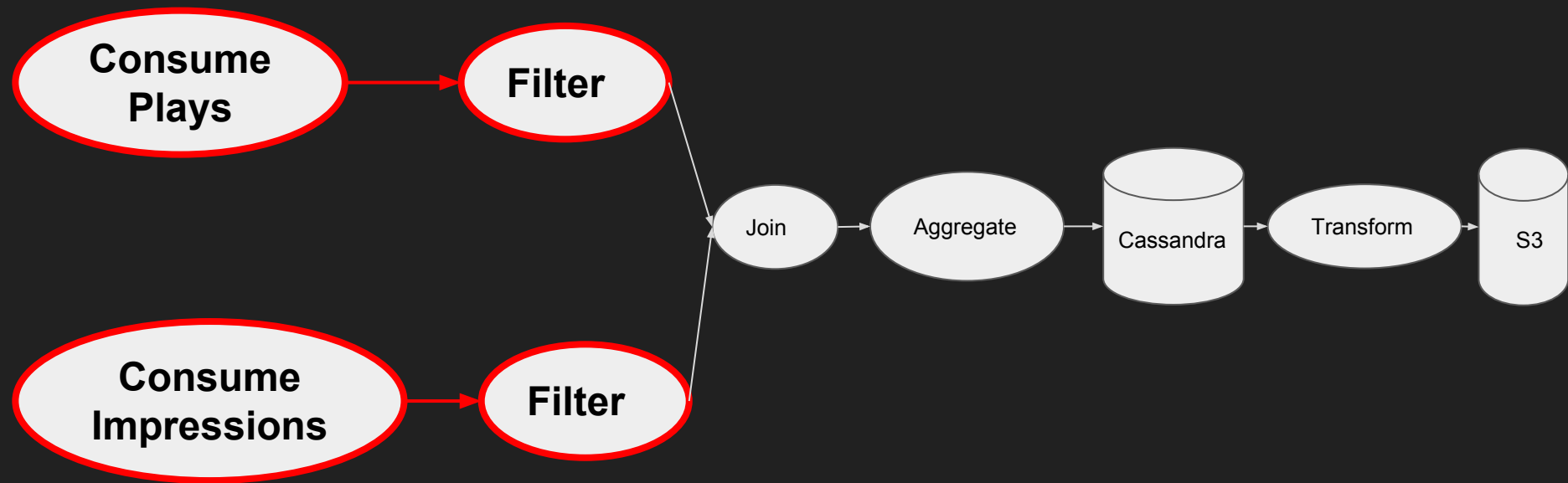
- Existing Spark infrastructure
- Experience with Spark
- Batch and Streaming

Components

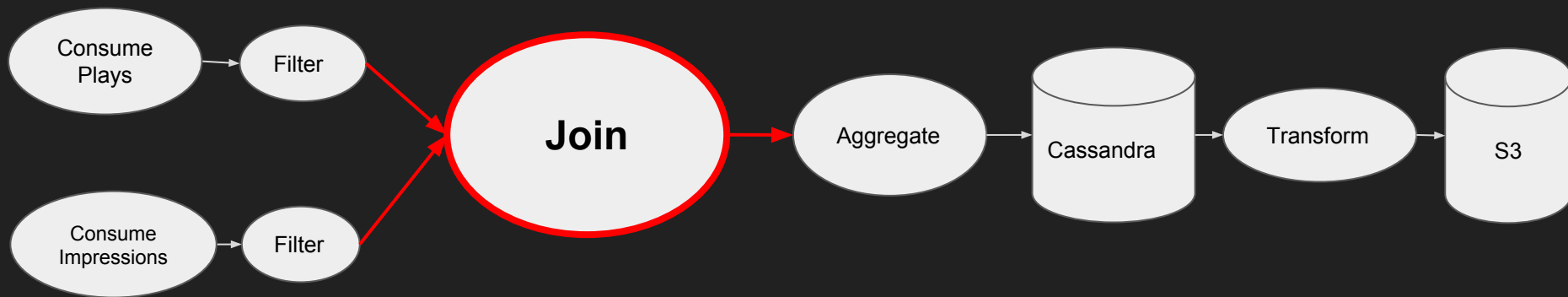


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Design



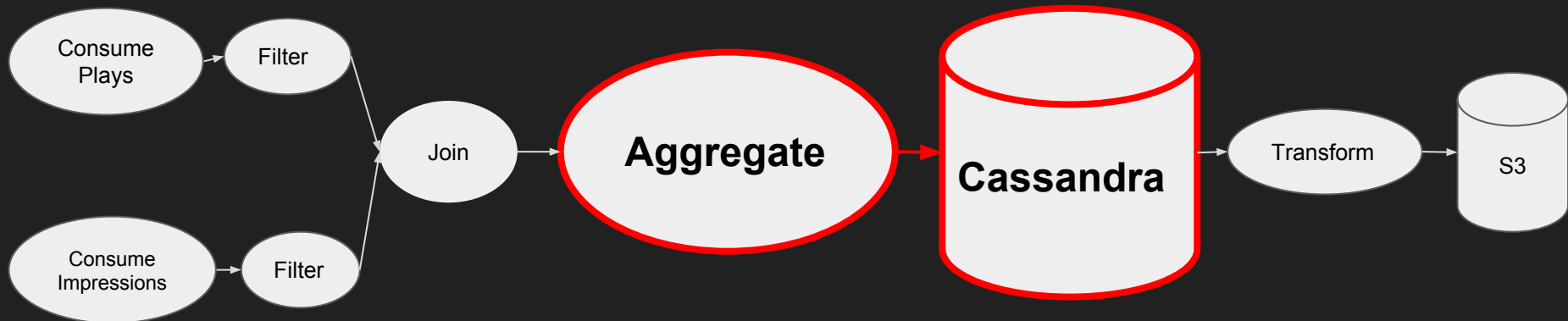
Design



Join Key

“Request Id” - a unique identifier of the source of a play or impression

Design



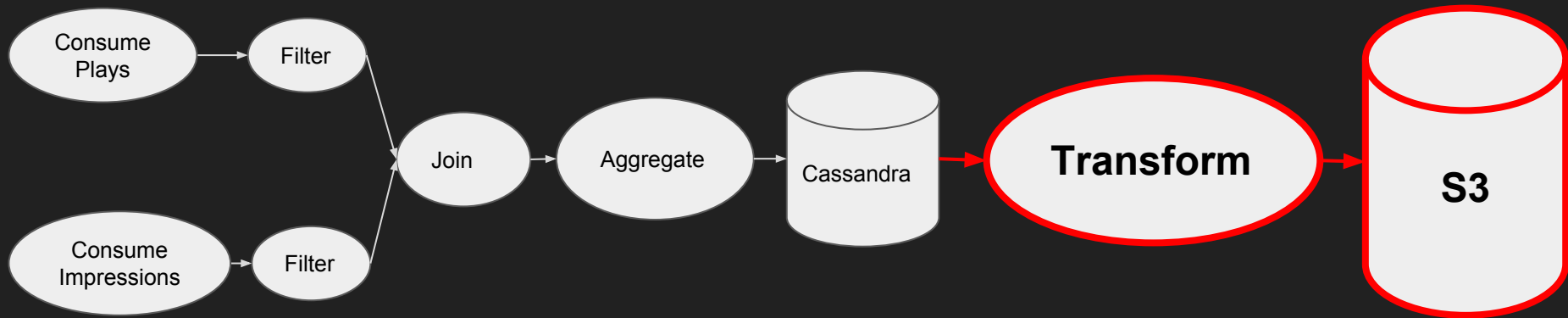
Output

Video	Epoch	Plays	Impressions
Stranger Things	1 (00:00-00:30)	4	5
Stranger Things	1 (00:00-00:30)	3	6
House Of Cards	2 (00:30-01:00)	8	10
Marseille	2 (00:30-01:00)	3	3

Output

- Instead of raw counts, output sets of request ids
 - Count = cardinality of the set of request ids
- Idempotent counting

Design



Programming with Spark Streaming

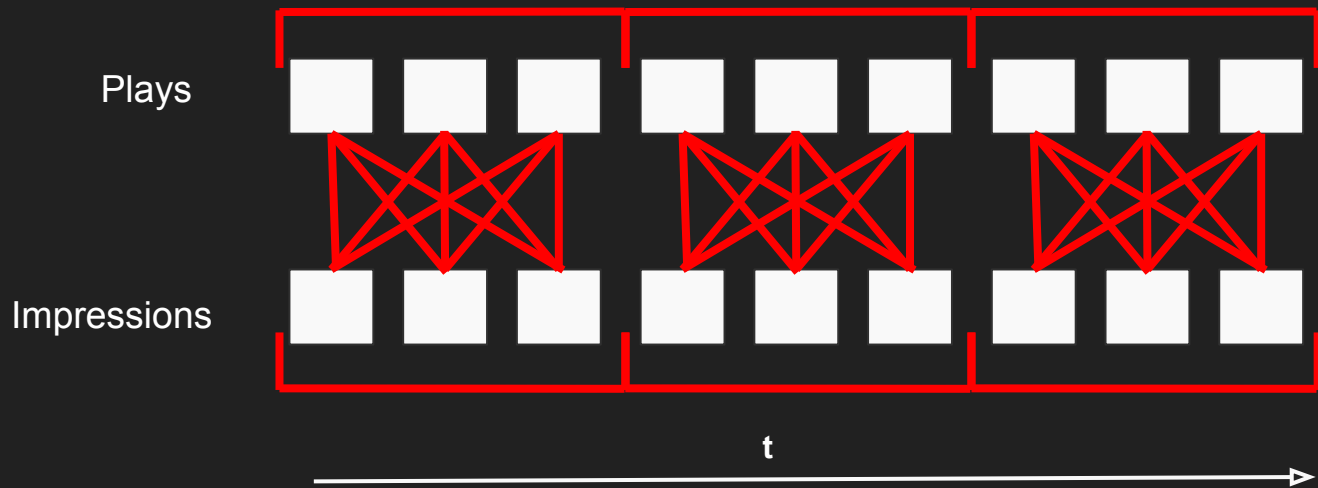
Streaming Joins

Streaming Joins - Time

- Time to browse and select a video
- Batched logging from client application
- Delays in data sources

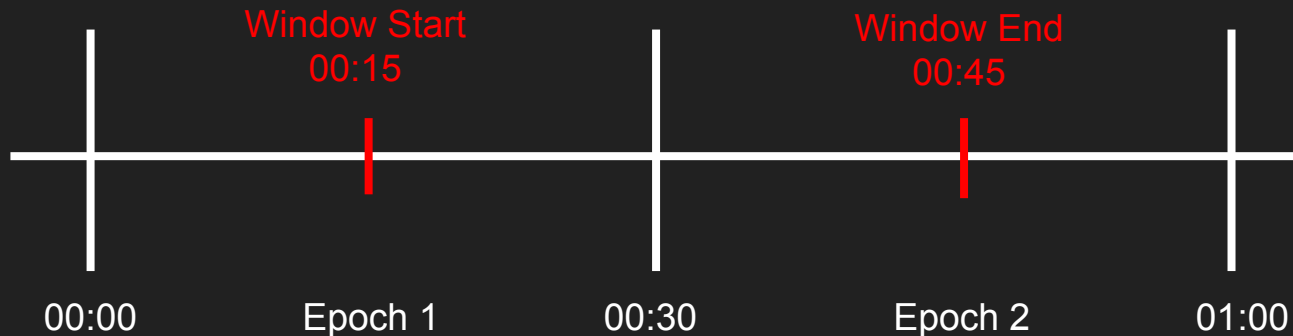
Streaming Joins - Attempt 1

- Window both plays and impressions by epoch duration
- Join the two windows together
- Slide by epoch duration



Streaming Joins - Attempt 1

- Easy to implement
- Tight coupling with processing time
- Does not mesh well with absolute time windows
- Failure can mean loss of all data for the entire window



Streaming Joins - Attempt II

- Join using mapWithState
- Join key is the mapWithState key
- State is the plays and impressions sharing the same join key
- Use timeouts to expire unjoined data

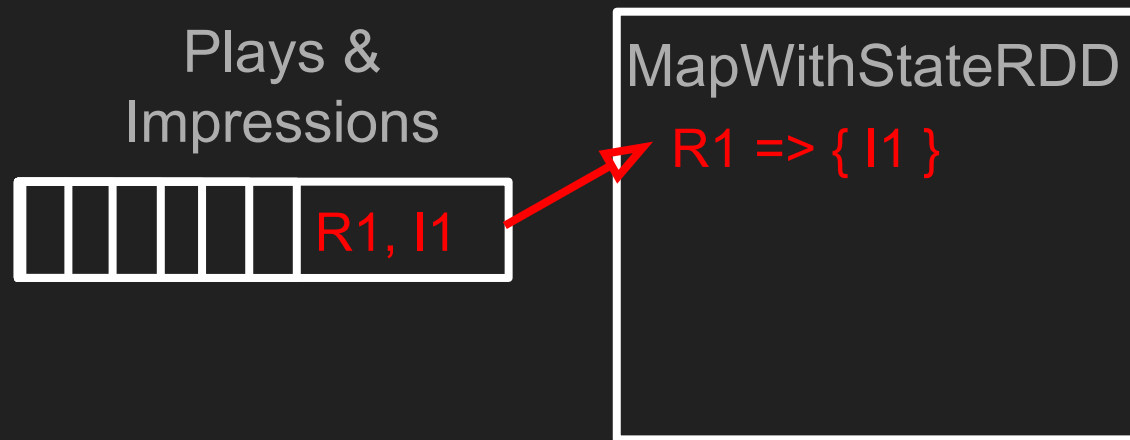
Streaming Joins - Attempt II

Plays &
Impressions



MapWithStateRDD

Streaming Joins - Attempt II



Streaming Joins - Attempt II

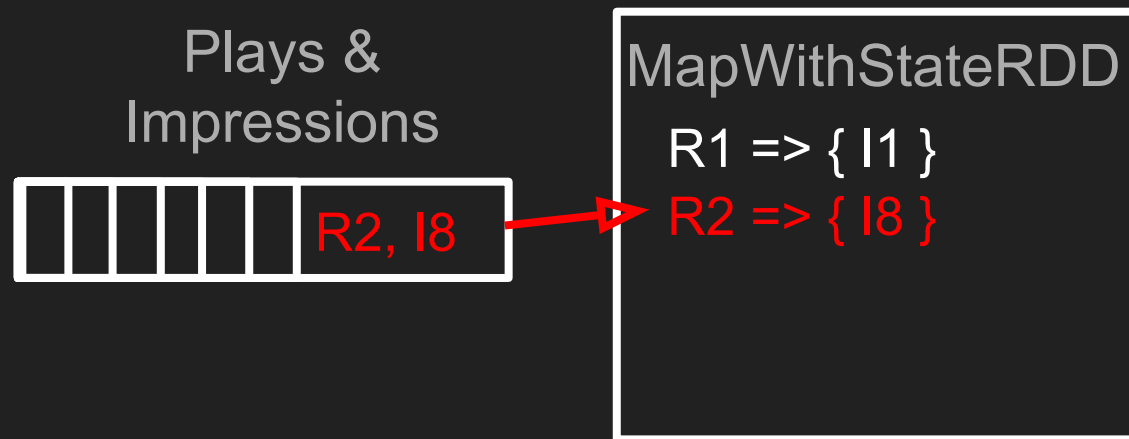
Plays &
Impressions



MapWithStateRDD

$R1 \Rightarrow \{ I1 \}$

Streaming Joins - Attempt II



Streaming Joins - Attempt II

Plays &
Impressions

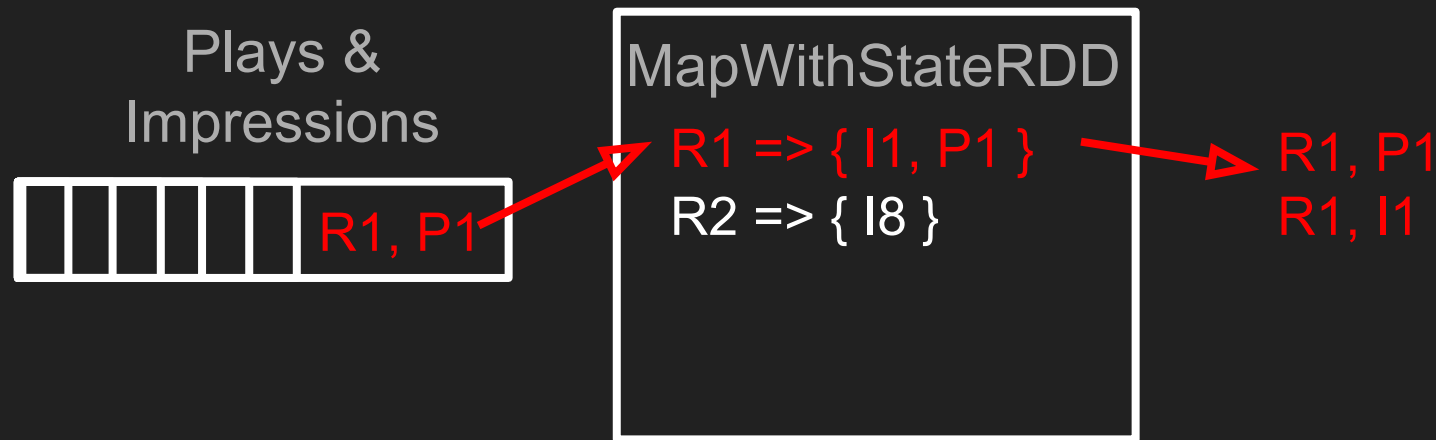


MapWithStateRDD

R1 => { I1 }

R2 => { I8 }

Streaming Joins - Attempt II



Streaming Joins - Attempt II

Plays &
Impressions

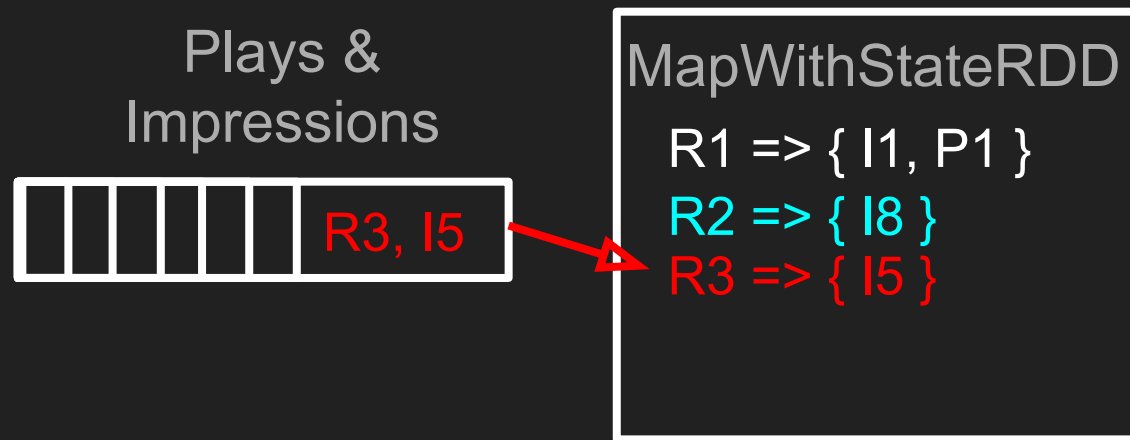


MapWithStateRDD

R1 => { I1, P1 }

R2 => { I8 }

Streaming Joins - Attempt II



Streaming Joins - Attempt II

Plays &
Impressions

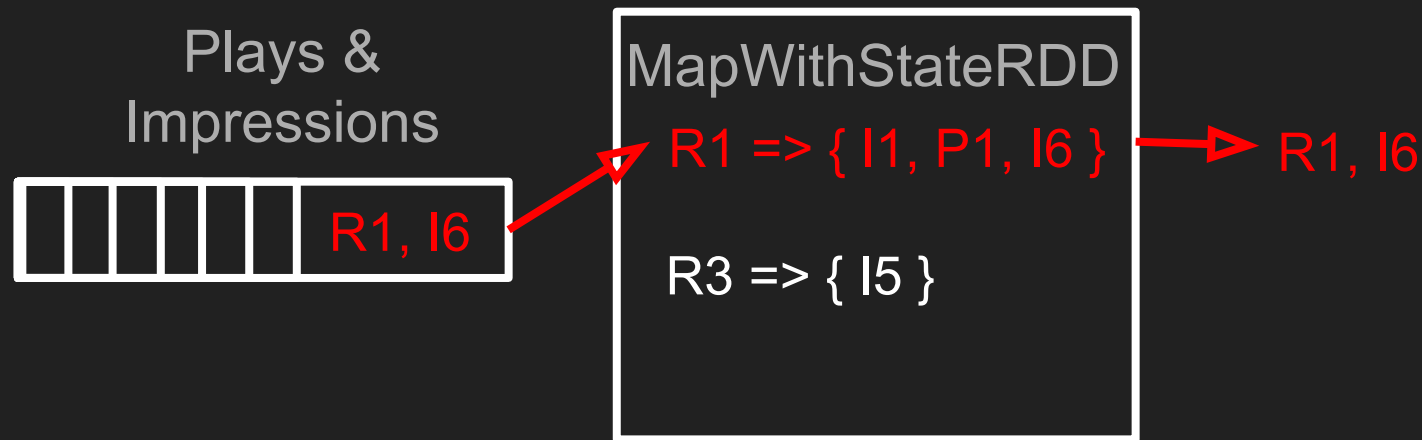


MapWithStateRDD

R1 => { I1, P1 }

R3 => { I5 }

Streaming Joins - Attempt II



Streaming Joins - Attempt II

Plays &
Impressions



MapWithStateRDD

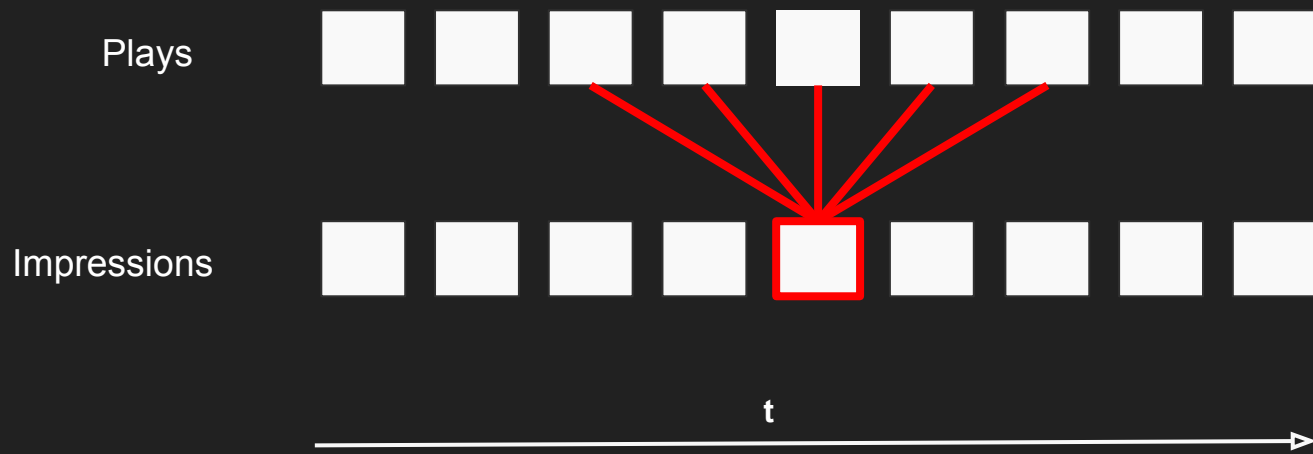
R1 => { I1, P1, I6 }

R3 => { I5 }

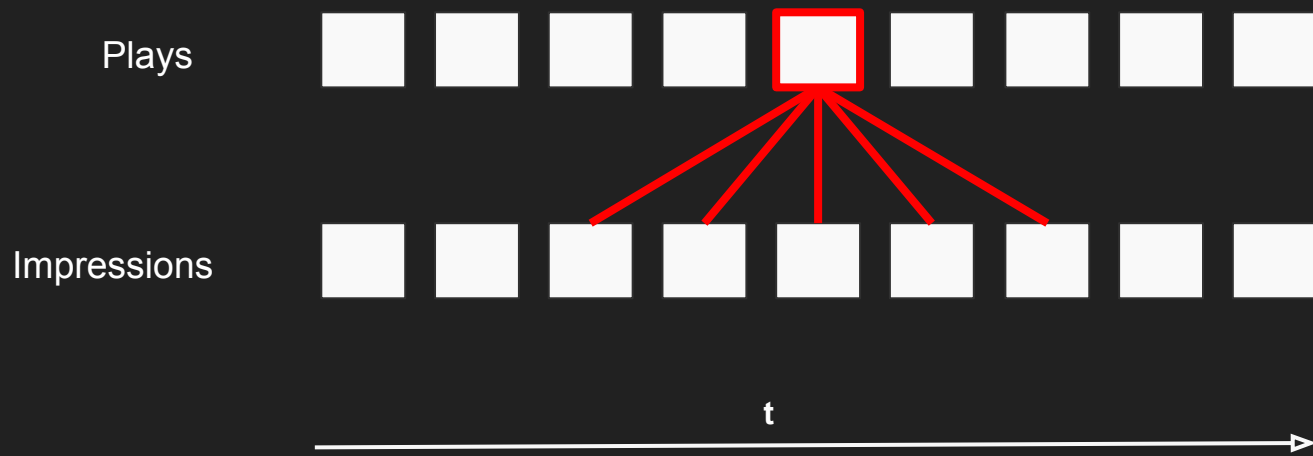
Streaming Joins - Attempt II

- Make progress every batch
- Too much “uninteresting” data
- High memory usage
- Large checkpoints

Streaming Joins - An Observation

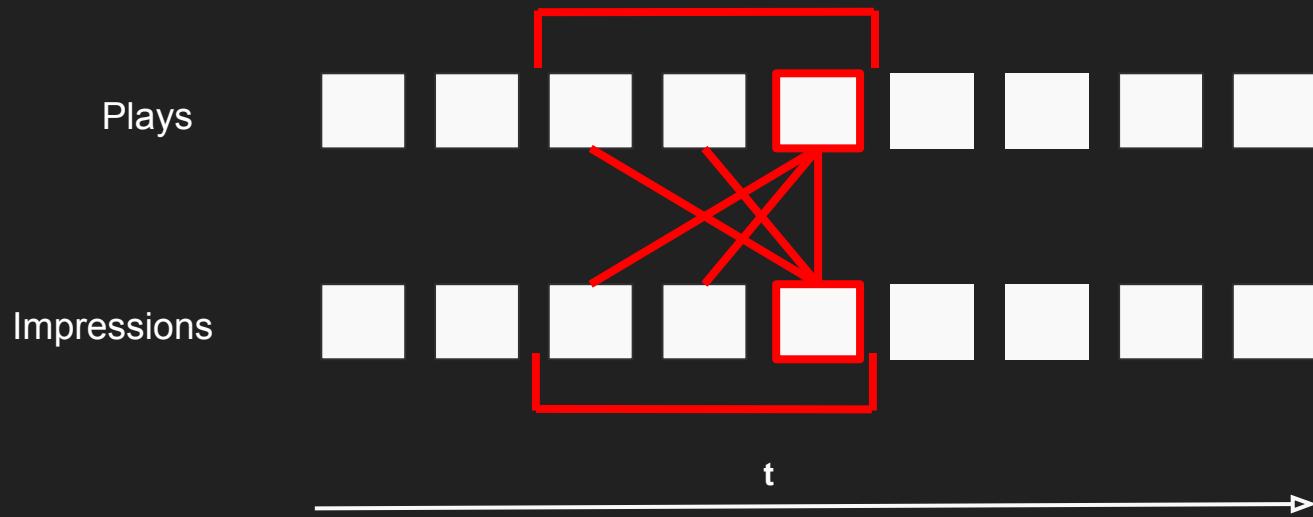


Streaming Joins - An Observation



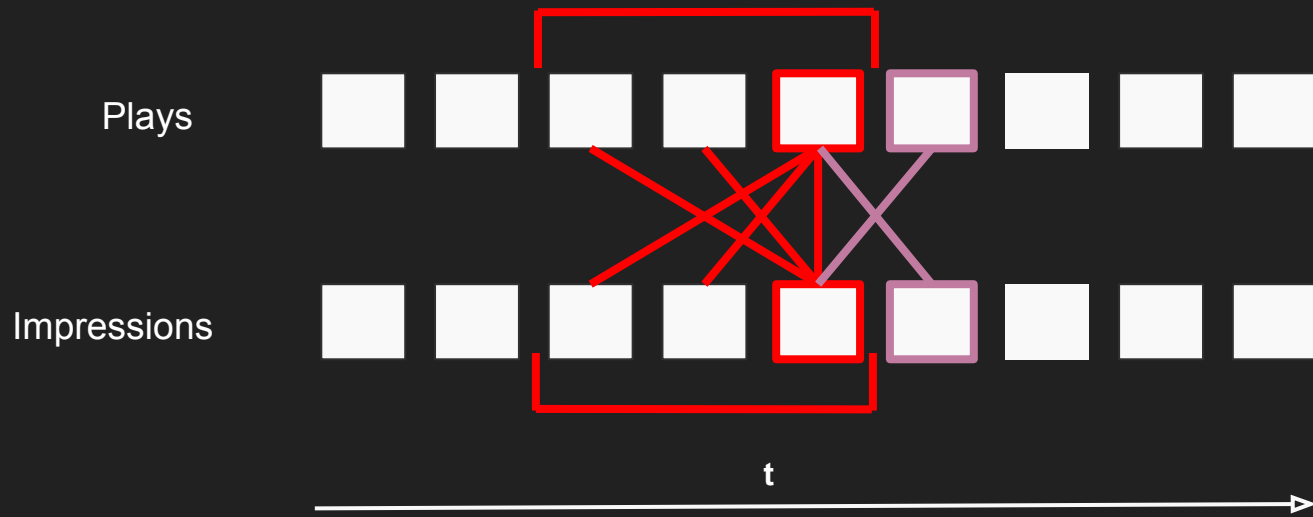
Streaming Joins - An Observation

Join incoming batch of plays to windowed impressions, and vice versa



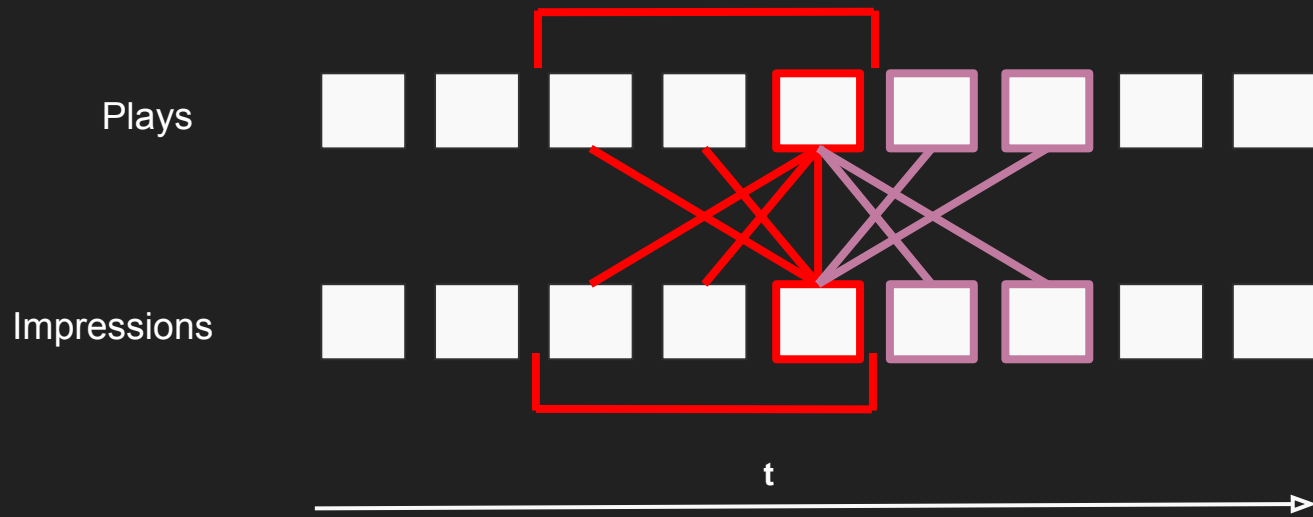
Streaming Joins - An Observation

Slide by batch interval...



Streaming Joins - An Observation

Slide by batch interval again...



Streaming Joins - Attempt III

- Counts are updated every batch
- Uses Spark's windowing
- No checkpoints

mapWithState

mapWithState

- Can be used for more than sessionization

mapWithState

- Can be used for more than sessionization
- Be aware of cache evictions
 - Lots of state may need to be recomputed

mapWithState

```
val input: DStream[(VideoId, RequestId)] = // ...  
val spec: StateSpec[VideoId, RequestId,  
                    Set[RequestId],  
                    (VideoId, Set[RequestId])] = // ...  
val output: DStream[(VideoId, Set[RequestId])] = {  
    input.  
        mapWithState(spec)  
}
```

mapWithState

```
val input: DStream[(VideoId, RequestId)] = // ...

val spec: StateSpec[VideoId, RequestId,
                    Set[RequestId],
                    (VideoId, Set[RequestId])] = // ...

val output: DStream[(VideoId, Set[RequestId])] = {
  input.
    mapWithState(spec).
    groupByKey.
    mapValues(_.maxBy(_.size))
}
```

mapWithState

```
val input: DStream[(VideoId, RequestId)] = // ...  
val spec: StateSpec[VideoId, Iterable[RequestId],  
                    Set[RequestId],  
                    (VideoId, Set[RequestId])] = // ...  
val output: DStream[(VideoId, Set[RequestId])] = {  
  input.  
    groupByKey.  
    mapWithState(spec)  
}
```

mapWithState

```
val input: DStream[(VideoId, RequestId)] = // ...  
  
val spec: StateSpec[VideoId, RequestId,  
                    Set[RequestId], Unit] = // ...  
  
val output: DStream[(VideoId, Set[RequestId])] = {  
  input.  
    mapWithState(spec).  
    stateSnapshots  
}
```

Productionizing Spark Streaming

Metrics

- Monitoring system health
- Aid in diagnosis of issues
- Needs to be performant and accurate

Metrics - Option I

- Use “traditional” stream processing metrics
 - Events/second, bytes/second, ...
- Batching can make numbers hard to interpret
- Susceptible to recomputation

Metrics - Option II

- Spark Accumulators
- Used internally by Spark
- Susceptible to recomputation
- Unclear when to report the metric
 - Can make use of SparkListener & StreamingListener

Metrics - Option III

- Explicit counts on RDDs
- Counts will be accurate
- Additional latency
- Use caching to prevent duplicate work*

Metrics

- Processing time < Batch interval
- Time the different parts of the job
 - Spark is lazy - may require forcing evaluation
- Use Spark UI metrics

Error Handling

- What exceptions cause the streaming job to crash?

Error Handling

- What exceptions cause the streaming job to crash?
 - Most seem to be caught to keep the job running
- Exception handling is application-specific
- Stop-gap: track the elapsed time since the batch started

Future Work

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- Red/Black deployment with zero data-loss

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- Auto-scaling

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- Auto-scaling
- Improved back pressure per topic

Future Work

- Red/Black deployment with zero data-loss
- Auto-scaling
- Improved back pressure per topic
- Updating broadcast variables

Questions?

We're hiring!

elliott@netflix.com

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