Spark Streaming At Bing Scale

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Scale

- Billions of search queries per month
- Hundreds of services power Bing stack
- Thousands of machines several Data Centers
- Tens of TBs of events per hour
- Several data processing frameworks



Data Curation

- Events of individual services little value
- Need correlation of events & curated datasets
 - at scale, on time, high fidelity
 - contributes directly to improving quality of services & monetization



Data Pipelines

- Traditionally implemented entirely using Batch processing in COSMOS infrastructure
 - Storage DFS (similar to HDFS)
 - Execution Dryad (general purpose, more expressive than map-reduce)
 - Query SCOPE (SQL 'style' scripting language that supports inline C#)
- Data pipelines are adopting near real-time processing – <u>new issues to address</u>



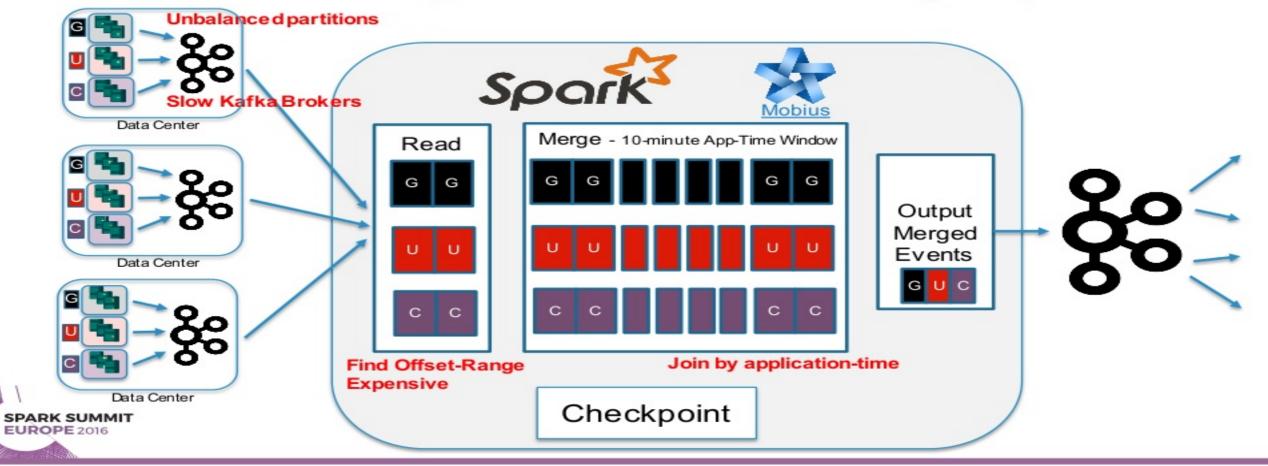
NRT Data Pipelines

Key issues to address in stream processing applications:

- Events generated in different DCs and at a rapid rate
- Events arrive out of order
- Events are delayed or get lost
- Managing state can be very expensive and hard to get right



NRT Processing Scenario – Event Merge Pipeline



Unbalanced Kafka Partitions

- Direct API Kafka partition maps to RDD partition
- Largest partition is the long pole in processing
- Solution
 - Repartition data from one Kafka partition into multiple RDDs w/o extra shuffling cost of DStream.Repartition()
 - Repartition threshold is configurable per topic
 - DynamicPartitionKafkaRDD.scala at github.com/Microsoft/Mobius



Slow Kafka Brokers

- Slow Kafka brokers increase batch time
- Delay in starting the next batch accumulates
- Solution
 - Submit Kafka data-fetch job on-time (defined by batch interval) in a separate thread, even when previous batch delayed
 - CSharpDStream.scala at github.com/Microsoft/Mobius



Find Offset-Range Expensive

- Finding Offset-range for {DC X Topic X Partition} is expensive
 - Several DCs 3 topics each average of 170 partitions per topic
 - {Get metadata + get offset range} took 10 mins for 2 min batch window
- {Metadata refresh + Find Offset} and data processing not parallel
- Solution
 - Move find offset-range to a separate thread
 - Materialize and cache Kafka RDD in that thread
 - DynamicPartitionKafkaInputDStream.scala at github.com/Microsoft/Mobius



Join By Application-Time

- Application-time based join not available in Spark 1.*
- Solution
 - Use custom join function in DStream.UpdateStateByKey()
 - Custom join function enforces time window based on application time
 - UpdateStateByKey maintains partially joined events as the state
 - PairDStreamFunctions.cs at github.com/Microsoft/Mobius



THANK YOU.



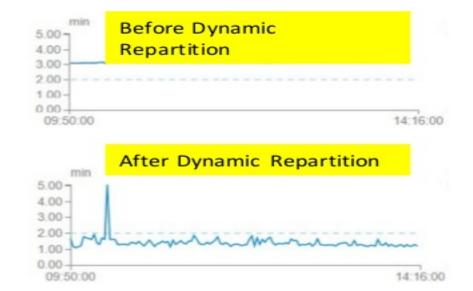
ADDITIONAL SLIDES



Dynamic Repartition

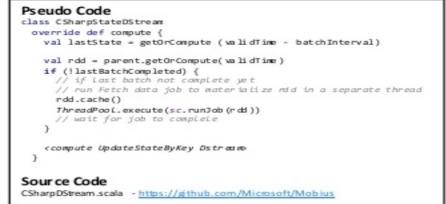
Pseudo Code class DynamicPartitionKafkaRDD(kafkaPartitionOffsetRanges) override def getPartitions { // repartition threshold per topic loaded from config val maxRddPartitionSize = Mapctopic, partitionSize> // apply max repartition threshold kafkaPartitionOffsetRanges.flatMap { case o => val rddPartitionSize = maxRddPartitionSize(o.topic) (o.fromOffset until o.untilOffset by rddPartitionSize).map(s => (o.topic, o.partition, s, (o.untilOffset, s + rddPartitionSize))) } Source Code DynamicPartitionKafkaRDD.scala - https://gbthub.com/McrosoftMobius

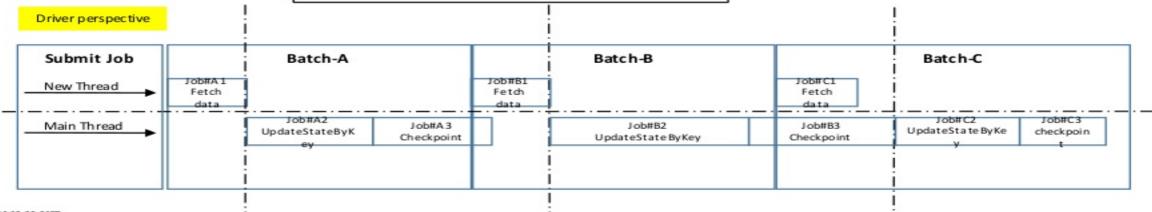






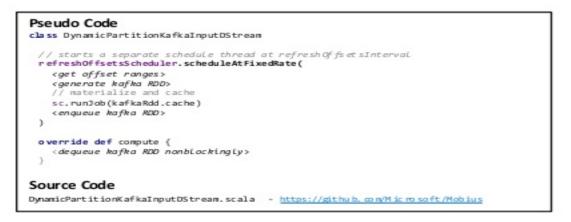
On-time Kafka fetch job submission

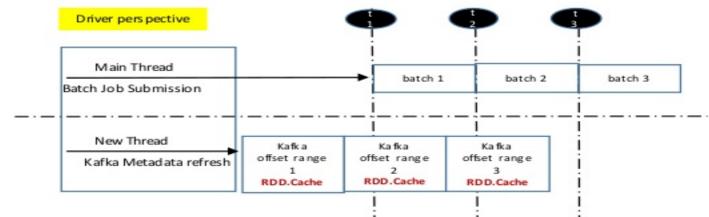




SPARK SUMMIT EUROPE 2016

Parallel Kafka metadata refresh + RDD materialization







Use UpdateStateByKey to join DStreams

