Summingbird:

A Framework for Integrating Batch and Online MapReduce Computations

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Scene:
Internet company in Silicon Valley (circa 2010)

Standard data science task:
What have people been clicking on?

Simple!

Write some Pig…

```
raw = load '/logs/' using LogLoader();

a = filter raw by action == 'click';
b = group a by target;
c = foreach b generate COUNT(a), group;

store c into 'counts/';
```

Or some Scalding (more recently)…

```
val input = TypedTsv[(String, String)]("/logs”)
val raw = TypedPipe.from(input)

raw.groupBy { case (target, action) => target }
  .size
  .write(TypedTsv("counts"))
```

Standard data science task:

What have people been clicking on?

Simple!

Now try:

What have people been clicking on *right now*?

grumble *ugh* *hrmmm*

Two major pain points (circa 2010):

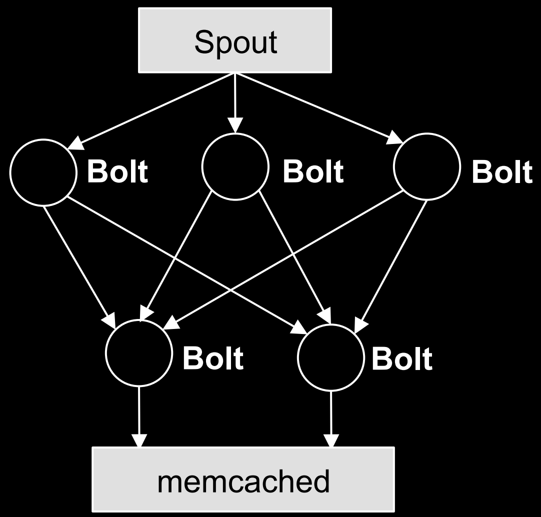
1. Lack of a standardized online processing framework
2. Having to write everything twice

State of the industry (circa 2013):

Good handle on batch processing at scale

Increasing convergence on online processing frameworks

Storm



Two major pain points:

1. Lack of a standardized online processing framework

✓ Widespread adoption of Storm at Twitter

2. Having to write everything twice

The point of this work…

Summingbird

A domain-specific language (in Scala) designed
to integrate batch and online MapReduce computations

Idea #1: Algebraic structures provide the basis for
seamless integration of batch and online processing

Idea #2: For many tasks, close enough is good enough
Probabilistic data structures as monoids

Summingbird

Primary goal is developer productivity
Optimizations can come later…

Scope: "the easy problems"

counting etc. (min, max, mean, moments…)
set membership
histograms

Batch and Online MapReduce

“map”

```
flatMap[T, U](fn: T => List[U]): List[U]

map[T, U](fn: T => U): List[U]

filter[T](fn: T => Boolean): List[T]
```

“reduce”

```
sumByKey
```

Idea #1: Algebraic structures provide the basis for seamless integration of batch and online processing

Semigroup = $(M , \oplus)$

$$\oplus : M \times M \longrightarrow M, \text{ s.t., } \forall m_1, m_2, m_3 \ni M$$

$$(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$$

Monoid = Semigroup + identity

$$\varepsilon \text{ s.t., } \varepsilon \oplus m = m \oplus \varepsilon = m, \ \forall m \ni M$$

Commutative Monoid = Monoid + commutativity

$$\forall m_1, m_2 \ni M, m_1 \oplus m_2 = m_2 \oplus m_1$$

Simplest example: integers with + (addition)

Idea #1: Algebraic structures provide the basis for seamless integration of batch and online processing

Summingbird values must be at least semigroups
(most are commutative monoids in practice)

Power of associativity =
You can put the parentheses anywhere!

$(a \oplus b \oplus c \oplus d \oplus e \oplus f)$	Batch = Hadoop
$(((((a \oplus b) \oplus c) \oplus d) \oplus e) \oplus f)$	Online = Storm
$((a \oplus b \oplus c) \oplus (d \oplus e \oplus f))$	Mini-batches

Results are exactly the same!

Summingbird Word Count

```
def wordCount[P <: Platform[P]]
  (source: Producer[P, String],
   store: P#Store[String, Long]) =
   source.flatMap { sentence =>
      toWords(sentence).map(_ -> 1L)
    }.sumByKey(store)
```

where data comes from

where data goes

"map"

"reduce"

Run on Scalding (Cascading/Hadoop)

```
Scalding.run {
  wordCount[Scalding](
    Scalding.source[Tweet]("source_data"),
    Scalding.store[String, Long]("count_out")
  )
}
```

read from HDFS

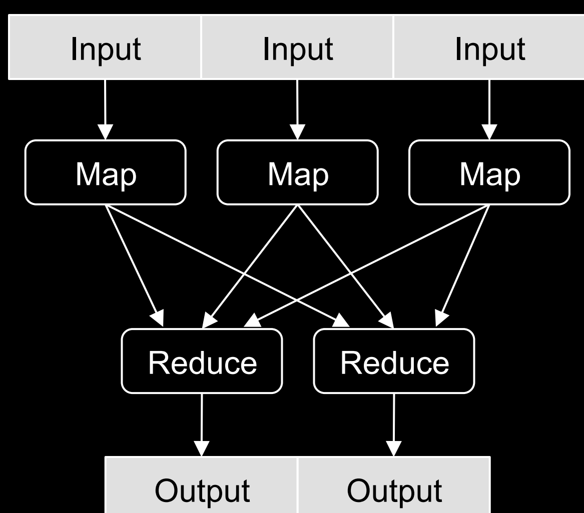
write to HDFS

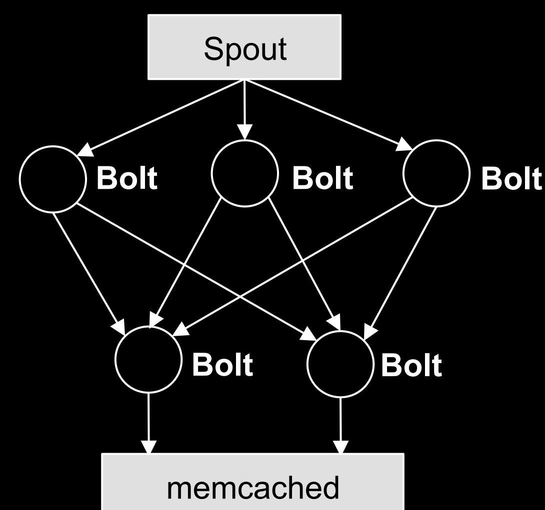
Run on Storm

```
Storm.run {
  wordCount[Storm](
    new TweetSpout(),
    new MemcacheStore[String, Long]
  )
}
```

read from message queue

write to KV store


Input
Input
Input
Map
Map
Map
Reduce
Reduce
Output
Output


Spout
Bolt
Bolt
Bolt
Bolt
Bolt
memcached

“Boring” monoids

addition, multiplication, max, min

moments (mean, variance, etc.)

sets

tuples of monoids

hashmaps with monoid values

More interesting monoids?

Idea #2: For many tasks, close enough is good enough!

“Interesting” monoids

Bloom filters (set membership)

HyperLogLog counters (cardinality estimation)

Count-min sketches (event counts)

Common features

1. Variations on hashing
2. Bounded error

Cheat sheet

	Exact	Approximate
Set membership	set	Bloom filter
Set cardinality	set	hyperloglog counter
Frequency count	hashmap	count-min sketches

Task: count queries by hour

Exact with hashmaps

```
def wordCount[P <: Platform[P]]
  (source: Producer[P, Query],
   store: P#Store[Long, Map[String, Long]]) =
   source.flatMap { query =>
      (query.getHour, Map(query.getQuery -> 1L))
    }.sumByKey(store)
```

Approximate with CMS

```
def wordCount[P <: Platform[P]]
  (source: Producer[P, Query],
   store: P#Store[Long, SketchMap[String, Long]])
  (implicit countMonoid: SketchMapMonoid[String, Long]) =
   source.flatMap { query =>
      (query.getHour,
       countMonoid.create((query.getQuery, 1L)))
    }.sumByKey(store)
```

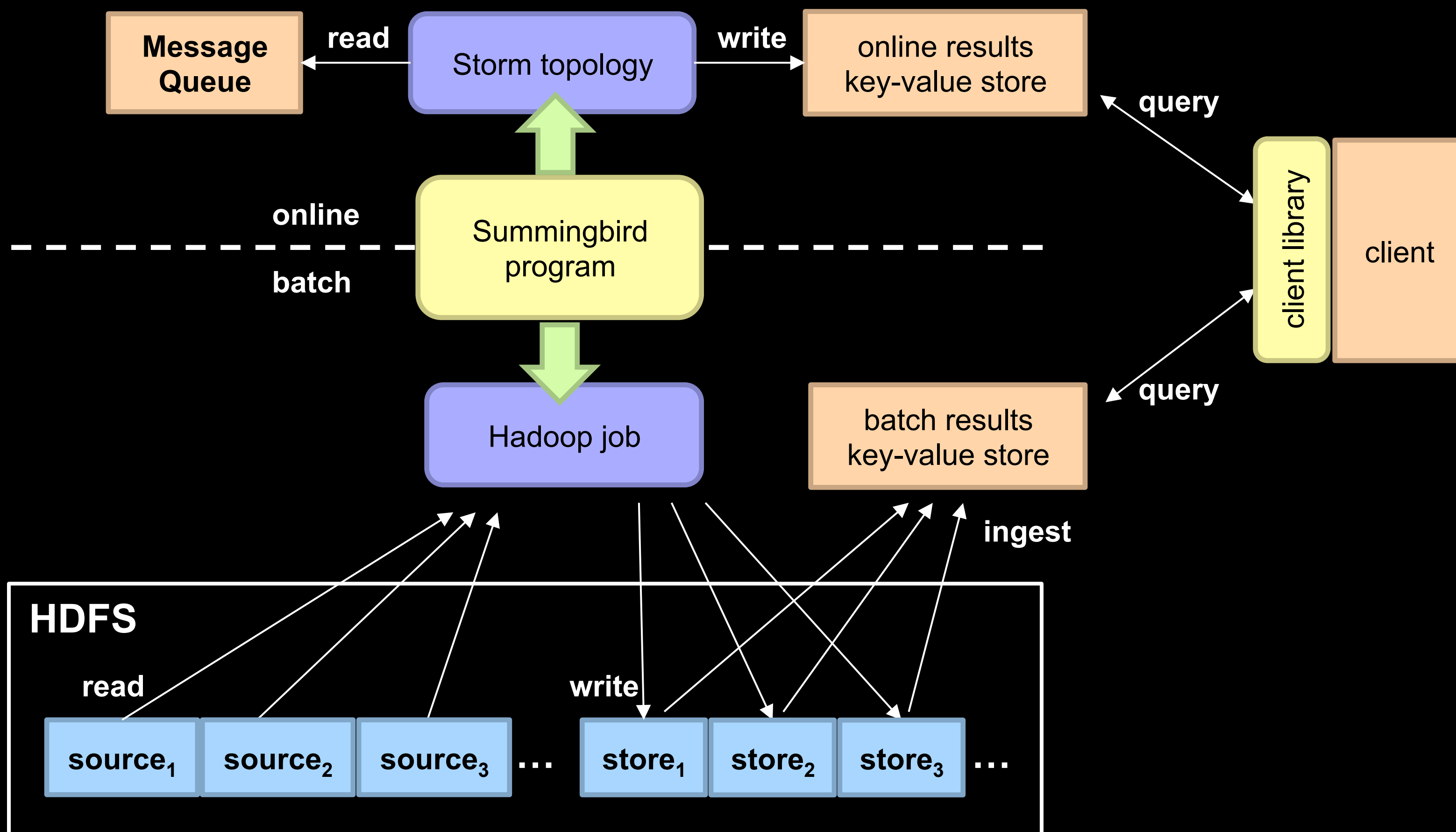
(Left) Joins

Task: count expanded URLs

```
def urlCount[P <: Platform[P]]
  (tweets: Producer[P, Tweet],
   urlExpander: P#Service[String, String],
   store: P#Store[String, Long]) =
   source.flatMap { tweet =>
      extractUrls(tweet.getText)
    }.map { url => (url, 1L) }
     .leftJoin(urlExpander)
     .map {
      case (shortUrl, (count, optResolvedUrl)) =>
        (optResolvedUrl.getOrElse("unknown"), count)
    }.sumByKey(store)
```

Hybrid Online/Batch Processing

Example: count historical clicks and clicks in real time



Deployment Status

Multiple generation of systems for "real-time counting"
(lots of experience on use cases)

Began late 2012
First production usage early 2013
Open-sourced Sept 2013

Currently:

A few dozen jobs, account for ~half of online analytics
Powers dashboards, signals for products

Related work

Lots of work on dataflow languages:
Pig, Scaling, DryadLINQ, Spark, etc.

Lots of work on online MapReduce:
HOP, DEDUCE, MapUpdate, etc.

Lots of work on incremental batch processing:
CBP, Incoop, Hourglass, etc.

Lots of work on stream processing:
Aurora, S4, Samza, BlockMon, Spark Streaming, MillWheel, Photon, etc.

Lots of work on pub-sub:
Kafka, RabbitMQ, SQS, etc.

Some work on category theory and big data:
monad comprehensions, monoids for ML, CRDT

Future Work

More target execution frameworks, e.g., Spark

Optimizations:
Standard “bag of tricks”
Automatic tuning of mini-batches for Storm

Summingbird

Integrating batch and online MapReduce

Idea #1: Algebraic structures provide the basis for seamless integration of batch and online processing

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Questions?