

# Turning Data into Value

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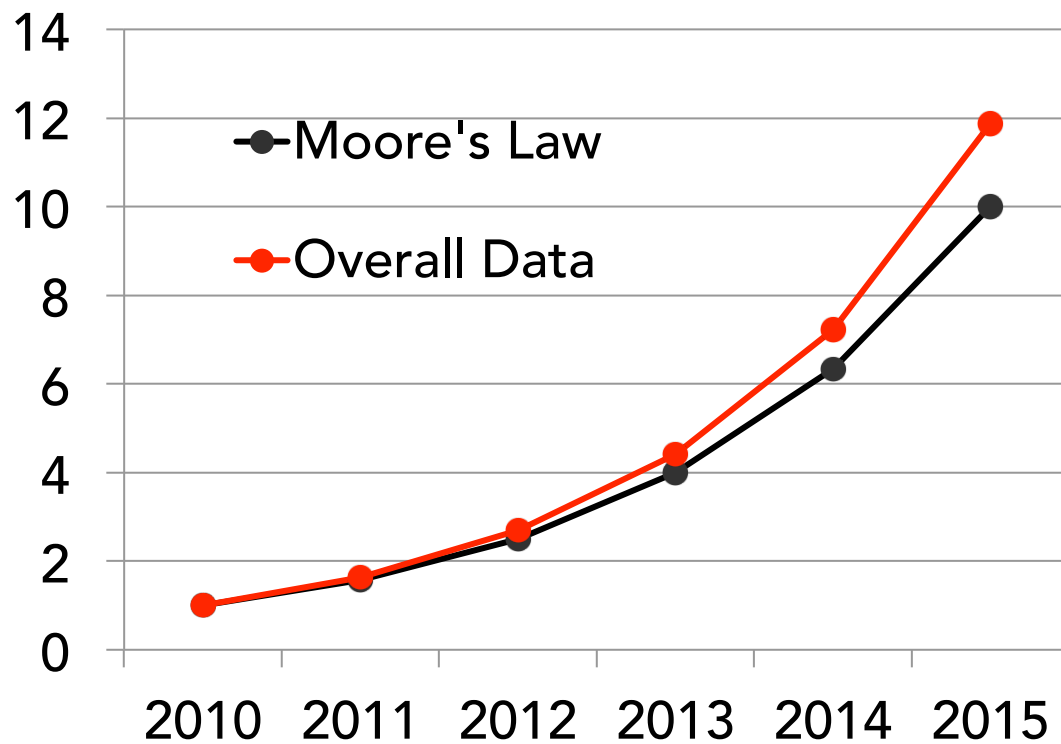
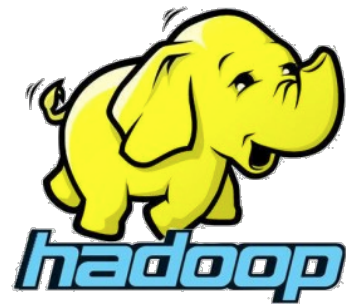
(also, UC Berkeley and Conviva)



# Data is Everywhere

Easier and cheaper than ever to collect

Data grows faster than Moore's law



(IDC report\*)

# The New Gold Rush

Everyone wants to extract value from data

» Big companies & startups alike



Huge potential

» Already demonstrated by Google, Facebook, ...

But, untapped by most companies

» “We have lots of data but no one is looking at it!”

# Extracting Value from Data Hard

Data is massive, unstructured, and dirty

Questions are complex

Processing, analysis tools still in their “infancy”

Need tools that are

- » Faster
- » More sophisticated
- » Easier to use

# Turning Data into Value

Insights, diagnosis, e.g.,

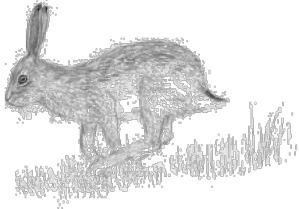
- » Why is user engagement dropping?
- » Why is the system slow?
- » Detect spam, DDoS attacks

Decisions, e.g.,

- » Decide what feature to add to a product
- » Personalized medical treatment
- » Decide when to change an aircraft engine part
- » Decide what ads to show

Data only as useful as the decisions it enables

# What do We Need?



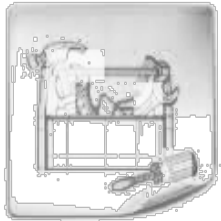
**Interactive queries:** enable faster decisions

» E.g., identify why a site is slow and fix it



**Queries on streaming data:** enable decisions on real-time data

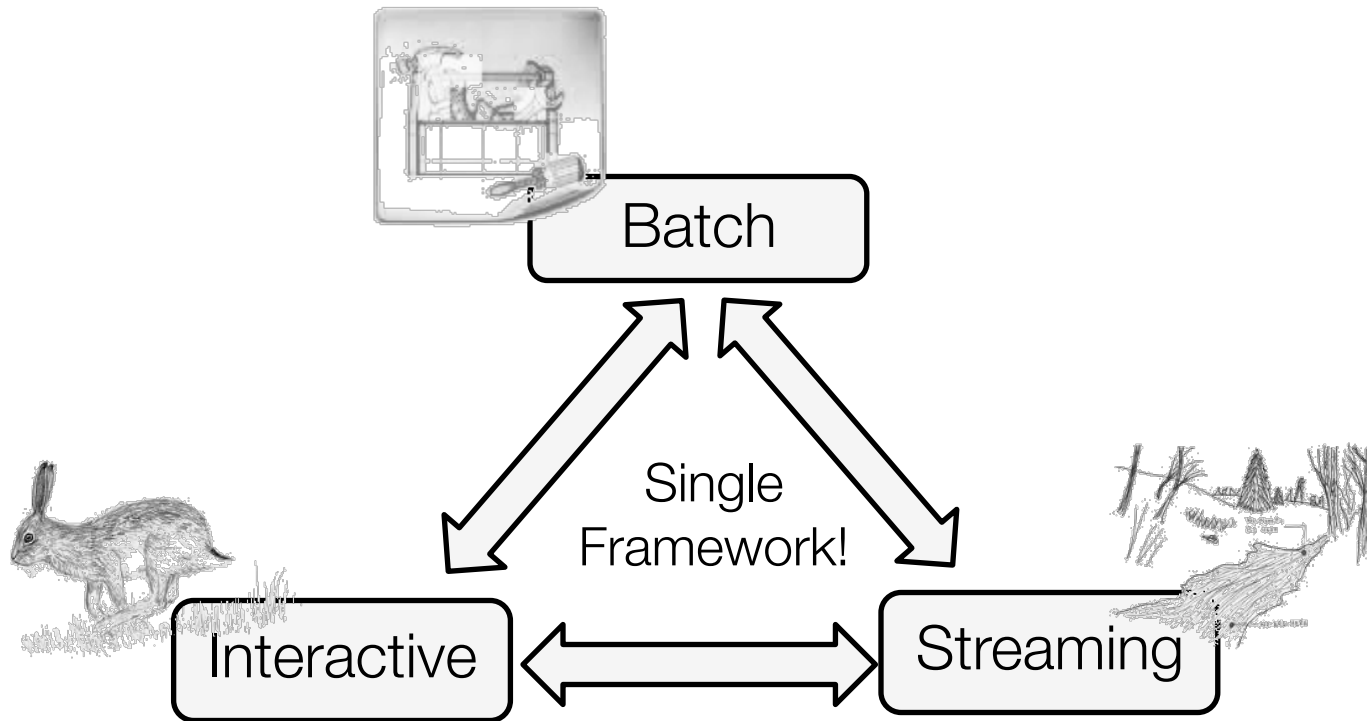
» E.g., fraud detection, detect DDoS attacks



**Sophisticated data processing:** enable “better” decisions

» E.g., anomaly detection, trend analysis

# Our Goal

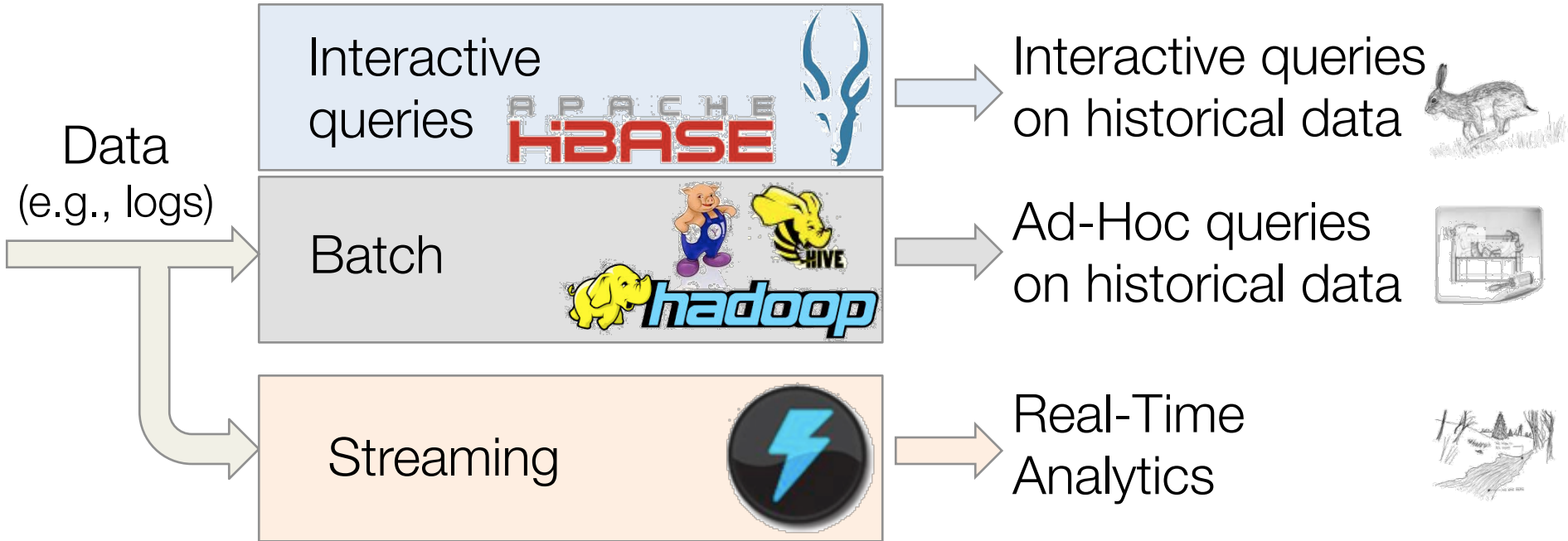


Support *batch*, *streaming*, and *interactive* computations...  
... in a unified framework

*Easy* to develop *sophisticated* algorithms (e.g., graph, ML algos)

# The Need For Unification

Today's state-of-art analytics stack



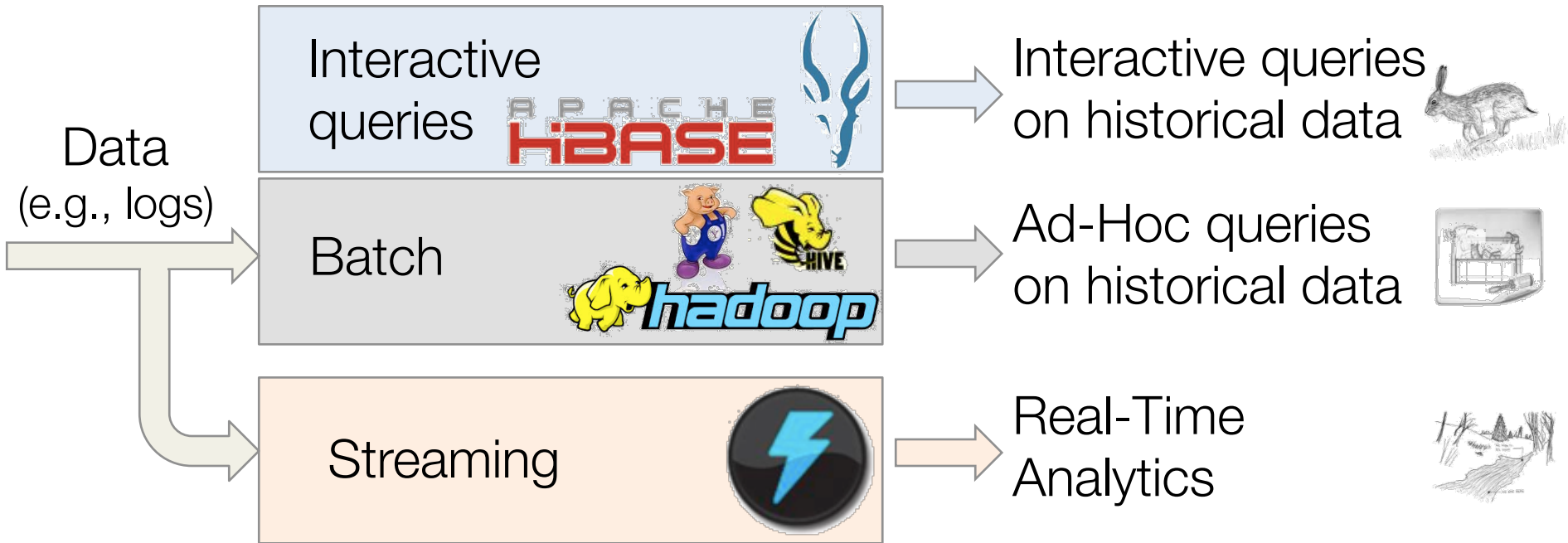
Challenge 1: need to maintain three stacks

- Expensive and complex
- Hard to compute consistent metrics across stacks



# The Need For Unification

Today's state-of-art analytics stack



Challenge 2: hard/slow to share data, e.g.,  
» Hard to perform interactive queries on streamed data

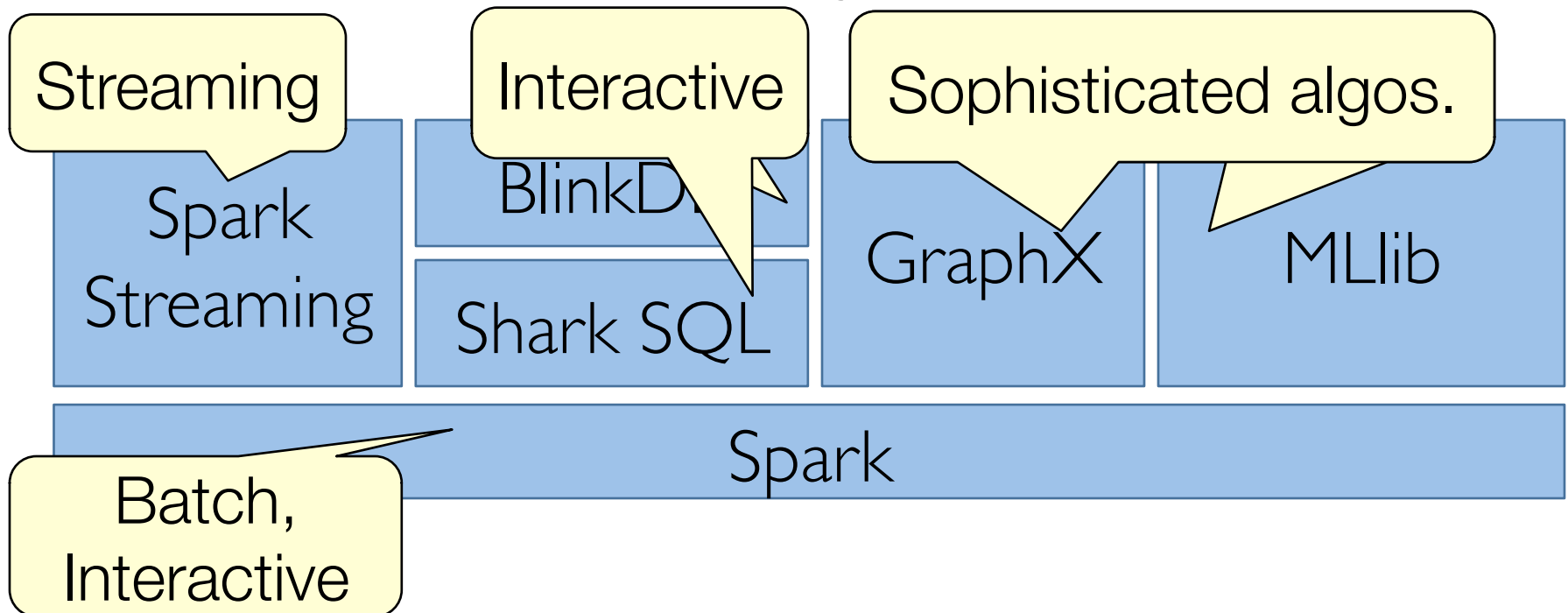
# Spark



Unifies *batch*, *streaming*, *interactive* comp.

Easy to build sophisticated applications

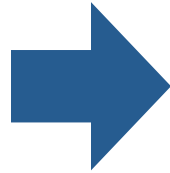
- » Support iterative, graph-parallel algorithms
- » Powerful APIs in Scala, Python, Java



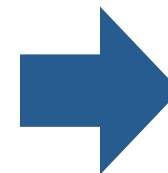
# An Analogy



First cellular phones



Specialized devices

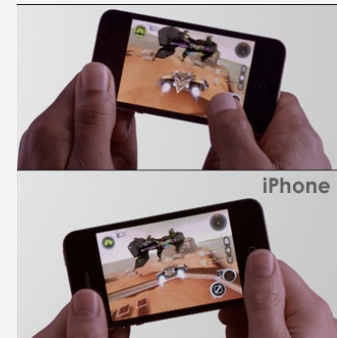
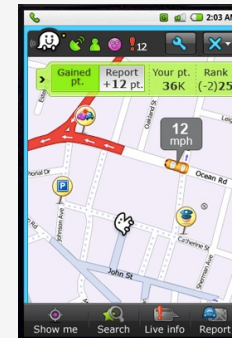


Unified device (smartphone)

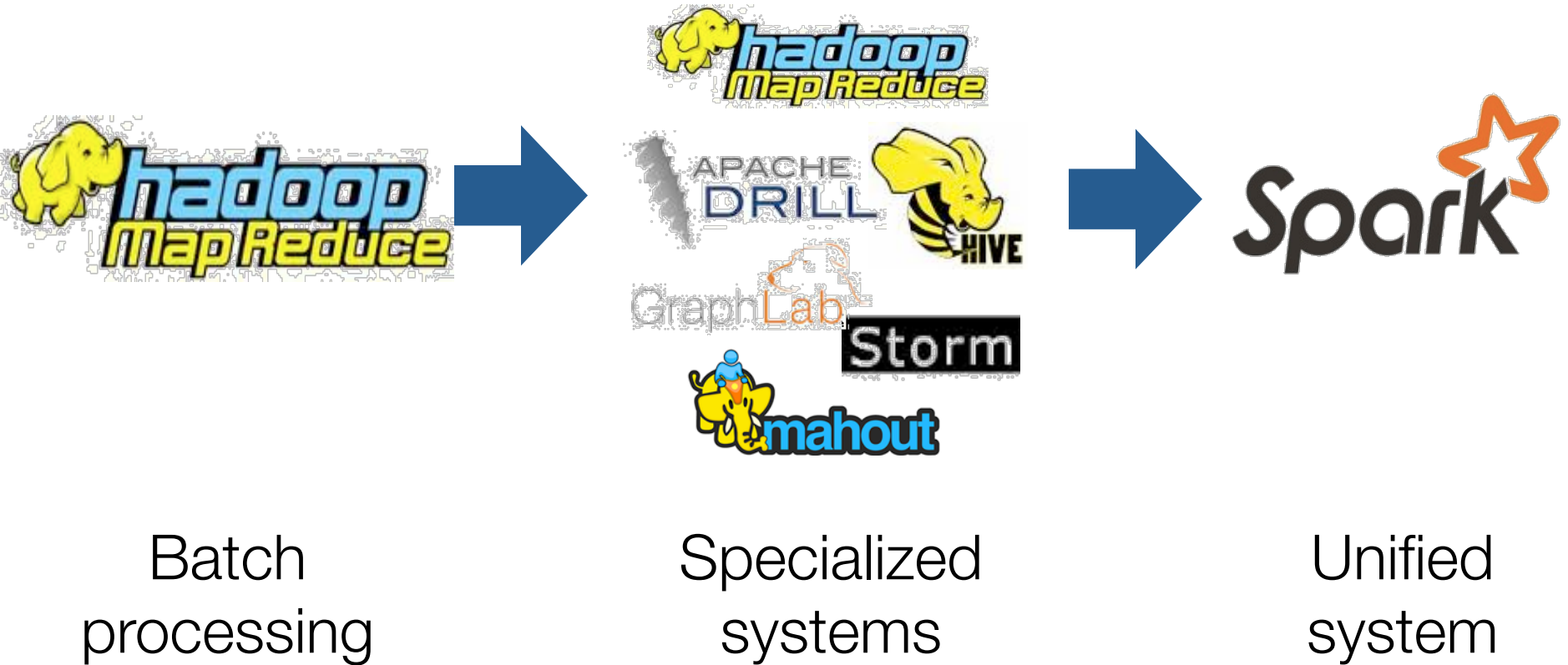
Better Phone

Better GPS

Better Games



# An Analogy



# Turning Data into Value, Examples

Unify real-time and historical data analysis

- » Easier to build and maintain
- » Cheaper to operate
- » Easier to get insights, faster decisions

Unify streaming and machine-learning

- » Faster diagnosis, decisions (e.g., better ad targeting)

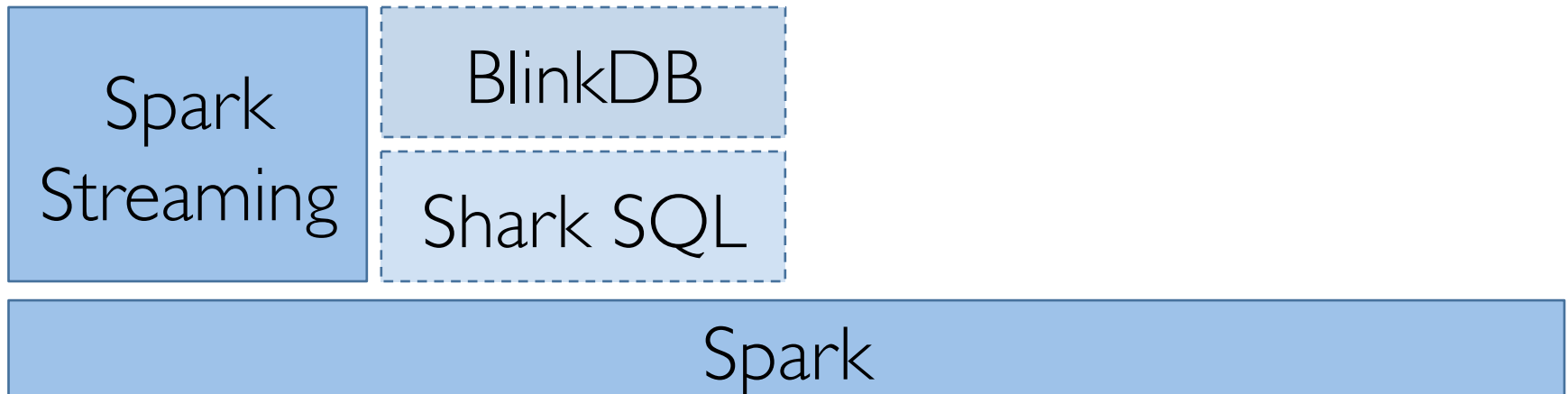
Unify graph processing and ETLs

- » Faster to get social network insights (e.g., improve user experience)

# Unify Real-time & Historical Analysis

Single implementation (stack) providing

- » Streaming
- » Batch (pre-computing results)
- » Interactive computations/queries



# Unify Real-time & Historical Analysis

Batch and streaming codes virtually the same

» Easy to develop and maintain consistency

*// count words from a file (batch)*

```
val file = sc.textFile("hdfs://.../pagecounts-*.gz")
```

```
val words = file.flatMap(line => line.split(" "))
```

```
val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)
```

```
wordCounts.print()
```

*// count words from a network stream, every 10s (streaming)*

```
val ssc = new StreamingContext(args(0), "NetCount", Seconds(10), ..)
```

```
val lines = ssc.socketTextStream("localhost", 3456)
```

```
val words = lines.flatMap(_.split(" "))
```

```
val wordCounts = words.map(x => (x, 1)).reduceByKey(_ + _)
```

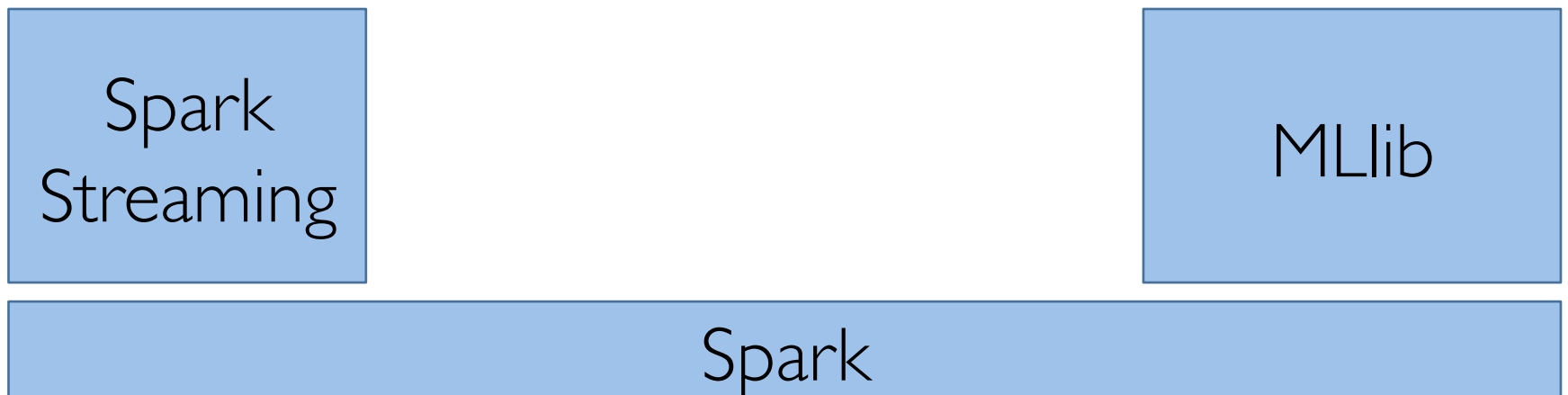
```
wordCounts.print()
```

```
ssc.start()
```

# Unify Streaming and ML

Sophisticated, real-time diagnosis & decisions,  
e.g.,

- » Fraud detection
- » Detect denial of service attacks
- » Early notification of service degradation and failures



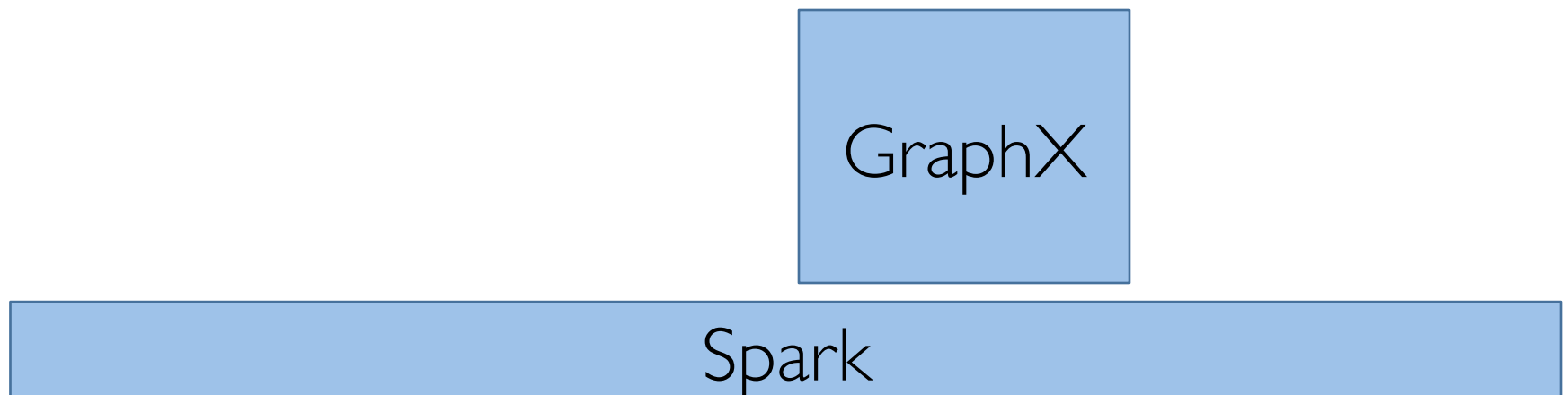


# Unify Graph Processing and ETL

Graph-parallel systems (e.g., Pregel, GraphLab)

- » Fast and scalable, but...
- » ... inefficient for graph creation, post-processing

GraphX: unifies graph processing and ETL



# Unify Graph Processing and ETL

Hadoop Graph Algorithms

Graph Creation (Hadoop)

Post  
Proc.

Graph Creation  
(Spark)

Post Proc.  
(Spark)

# “Crossing the Chasm”



AWS Products & Solutions ▾

## Databricks aims to build next-generation analytic tools for Big Data

A new startup will accelerate the maturation of the Berkeley Data Analytics Stack

[Databricks](#) | [@bigdata](#) | [Comment](#) | September 25, 2013

## New Cloudera Partner Program Harnesses Power of Innovative Startups Databricks, the Inaugural Partner of Cloudera Connect: Innovators, Teams With Cloudera for High-Speed Data Analytics

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2013-10-28 12:10:03 -



Print article

## WANDisco Announces Support for In-Memory Data Processing Technologies, Spark and Shark



Press Release: WANDisco, Plc. – Wed, Jun 26, 2013 9:00 AM EDT

# Cloudera Partnership

Integrate Spark with Cloudera Manager

Spark will become part of CDH

Enterprise class support and professional services available for Spark



# We are Committed to...

... open source

» We believe that any successful analytics stack will be open source

... improve integration with Hadoop

» Enable every Hadoop user take advantage of Spark

... work with partners to make Apache Spark successful for enterprise customers



# Summary

Everyone collects but few extract value from data

Unification of comp. and prog. models key to

- » Efficiently analyze data
- » Make sophisticated, real-time decisions

Spark is unique in unifying

- » batch, interactive, streaming computation models
- » data-parallel and graph-parallel prog. models

Many use cases in the rest of the program!

