From pipelines to refineries: scaling big data applications

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About Me

- Tim Hunter
- Software engineer @ Databricks
- Ph.D. from UC Berkeley in Machine Learning
- Very early Spark user
- Contributor to MLlib
- Author of TensorFrames and GraphFrames

Introduction

- Spark 2.2 in the release process
- Spark 2.3 being thought about
- This is the time to discuss Spark 3
- This presentation is a personal perspective on a future Spark

Introduction

There is nothing more practical than a good theory.

James Maxwell

As Spark applications grow in complexity, what challenges lie ahead.

Can we find some good foundations for building big data frameworks?

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What category does Spark live in?

A monad?

A functor?

An applicative?

Introduction

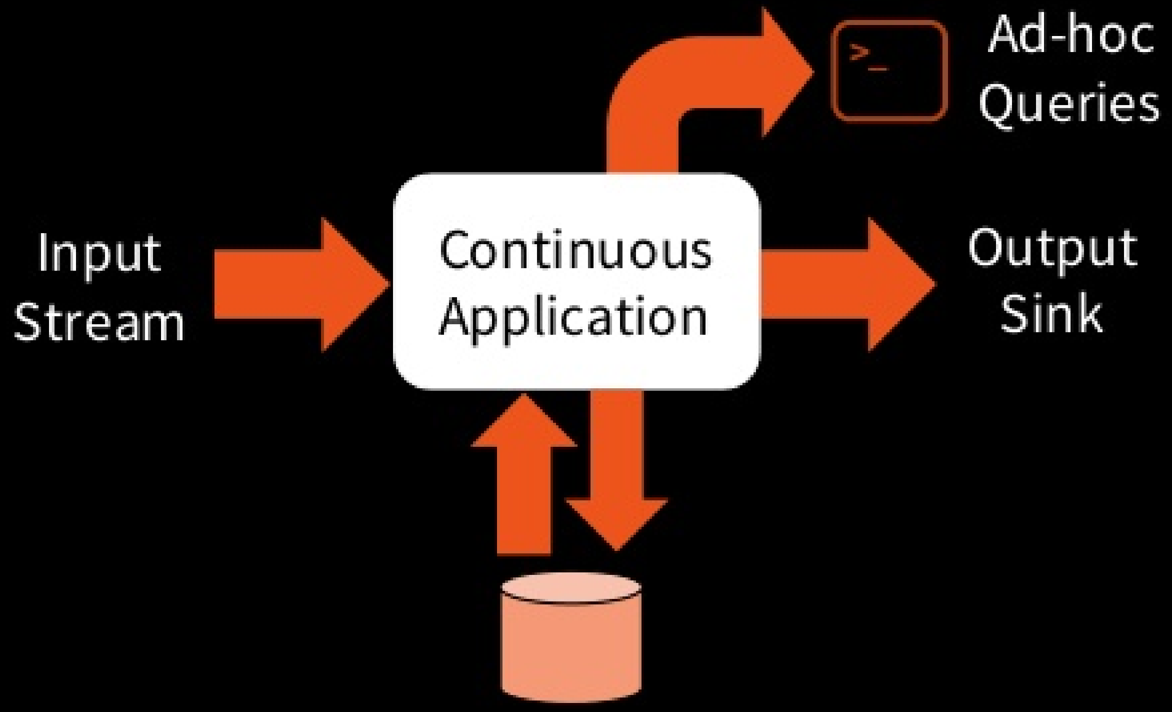
- Anything presented here can be implemented in a modern programming language
- No need to know Haskell or category theory

Outline

- State of the union
  - What is good about Spark?
  - What are the trends?
- Classics to the rescue
  - Fighting the four horsemen of the datapocalypse
  - Laziness to the rescue
- From theory to practice
  - Making data processing great again

State of the union

- What we strive for



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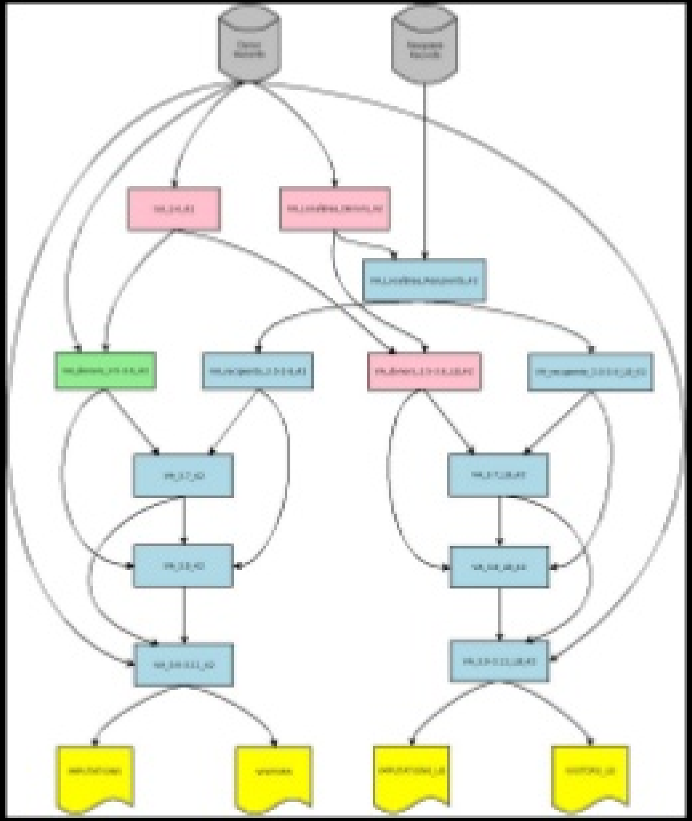
State of the union

- What we deal with:
  - Coordinating a few tasks



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State of the union

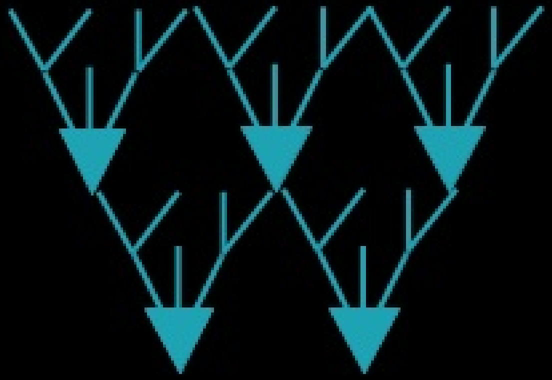
- The (rapidly approaching) future
  - Thousands of input sources
  - Thousands of concurrent requests
  - Mixing interactive, batch, streaming

- How do we enable this?

The state of the union

- The image of a pipeline gives you the illusion of simplicity
  - One input and one output

- Current big data systems: the tree paradigm
  - Combine multiple inputs into a single output
  - The SQL paradigm
  - Followed by Spark



- A forest is more than a set of trees
  - Multiple inputs, multiple outputs
  - The DAG paradigm

Data processing as a complex system

- Orchestrating complex flows is nothing new:
  - Tracking and scheduling: Gantt, JIRA, etc.
  - Build tools: Bazel (Blaze), Pants, Buck
  - General schedulers: AirFlow, FBLearner, Luigi
- Successfully used for orchestrating complex data processing
- But they are *general* tools:
  - They miss the fact that we are dealing with *data* pipelines
  - Separate system for scheduling and for expressing transforms
  - No notion of schema, no control of the side effects

Data processing as a complex system

- Any software becomes an exercise in managing complexity.
  - Complexity comes from interactions
  - How to reduce interactions?
- How to build more complex logic based on simpler elements?
  - How to compose data pipelines?
- Continuous evolution
  - Let's change the engines in mid-flight, because it sounds great

The ideal big processing system:

- *Scalability*
  - in quantity (big data) and diversity (lots of sources)
- *Chaining*
  - express the dependencies between the datasets
- *Composition*
  - assemble more complex programs out of simpler ones

- *Determinism*
  - given a set of input data, the output should be unique*
- *Coffee break threshold*
  - quick feedback to the user

How is Spark faring so far?

- You *can* do it, but it is not easy
- Spark includes multiple programming models:
- The RDD model: low-level manipulation of distributed datasets
  - Mostly imperative with some lazy aspects
- The Dataset/Dataframes model:
  - Same as RDD, with some restrictions and a domain-specific language
- The SQL model: only one output, only one query

What can go wrong with this program?

```
all_clicks = session.read.json("/tables/clicks/year=2017")
all_clicks.cache()
max_session_duration = all_clicks("session_duration").max()
top_sessions = all_clicks.filter(
            all_clicks("session_duration") >= 0.9 * max_session_duration)
top_ad_served = top_sessions("ad_idd")
top_ad_served.write.parquet("/output_tables/top_ads")
```

leak

a few hours…

typo

missing directory

The 4 horsemen of the datapocalypse

- Eager evaluation
- Missing source or sink
- Resource leak
- Typing (schema) mismatch

Classics to the rescue

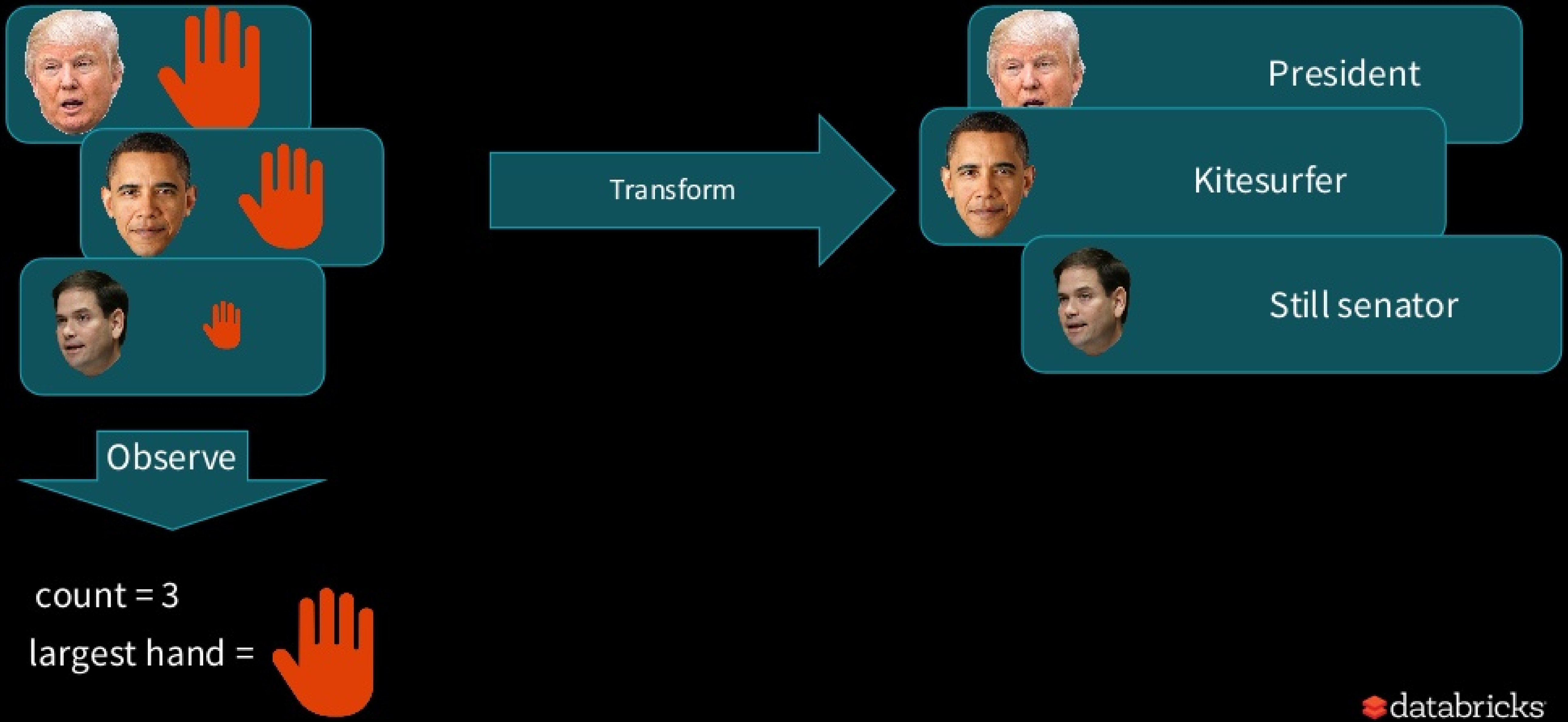
Theoretical foundations for a data system

- A dataset is a collection of elements, all of the same type
  - Scala: Dataset[T]

- Principle: the content of a dataset cannot be accessed directly
  - A dataset can be *queried*

- An observable is a single element, with a type
  - intuition: dataset with a single row
  - Scala: Observable[T]

Theoretical foundations for a data system



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Theoretical foundations for a data system

- *Principle*: the observation only depends on the content of the dataset
  - You cannot observe partitions, ordering of elements, location on disk, etc.

- Mathematical consequence: all reduction operations on datasets are monoids:
  - $f(A \cup B) = f(A) + f(B) = f(B) + f(A)$
  - $f(\text{empty}) = 0$

Theoretical foundations for a data system

- *Principle*: closed world assumption
  - All the effects are modeled within the framework
  - The inputs and the transforms are sufficient to generate the outputs
- Practical consequence: strong checks and sci-fi optimizations

Examples of operations

- They are what you expect:
  - Dataset[Int] : a dataset of integers
  - Observable[Int] : an observation on a dataset
- max: Dataset[Int] => Observable[Int]
- union: (Dataset[Int], Dataset[Int]) => Dataset[Int]
- collect: Dataset[Int] => Observable[List[Int]]

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- An implementation of these principles on top of Spark (Haskell + Scala)
- It outputs a graph of logical plans for Spark (or other systems)
- Follows the compiler principle:
  - I will try to prove you wrong until you have a good chance of being right
- Karps makes a number of correctness checks for your program
- It acts as a global optimizer for your pipeline

Demo 1

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This is useless!

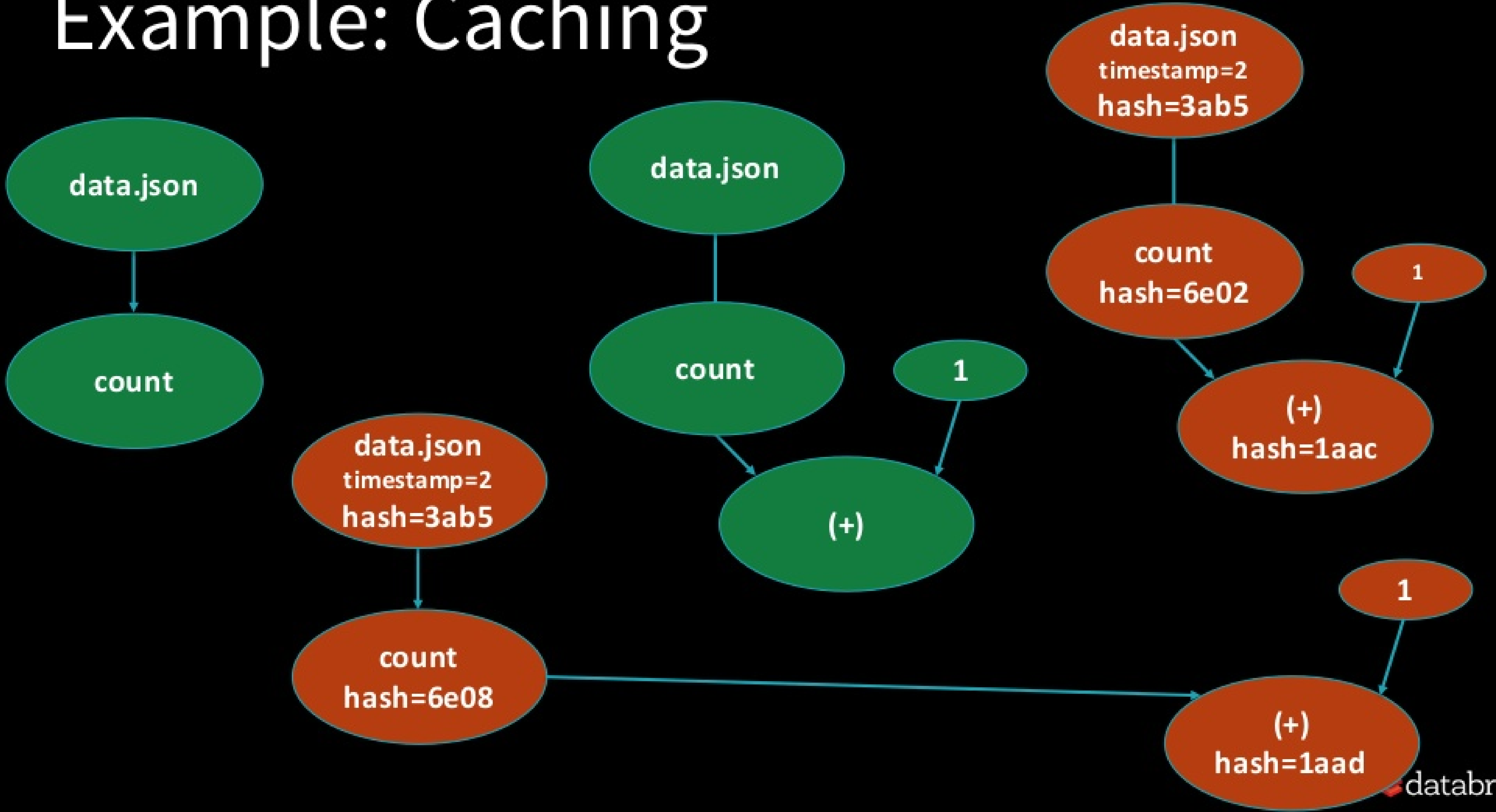
- Lazy construction of very complex programs
- Most operations in Spark can be translated to a small set of primitive actions with well-defined composition rules.
- The optimizer can then rewrite the program without changing the outcome
- Optimizations can leverage further SQL optimizations

Dealing with In and Out

- The only type of I/O: read and write datasets
- This is an observable
- Operations are deterministic + results are cached
  - -> only recompute when the data changes

- Demo

Example: Caching



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Example: graph introspection

Future directions

- Python interface (interface + pandas backend)
- Writer module
- Finish GroupBy (cool stuff ahead)
- SQL (simple and cool stuff to do in this area)

Conclusion: trends in data processing

- How to manage the complexity of data flows?
- Taking inspiration from the functional world
- Spark provides solid foundation
- Laziness, declarative APIs alleviate complexity

Trying this demo

- https://github.com/krapsh/kraps-haskell
- Notebooks + Docker image:
  - https://github.com/krapsh/kraps-haskell/tree/master/notebooks
- Server part (scala):
  - https://github.com/krapsh/kraps-server

Discount code: BayAreaMU

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