It’s a StreamER World

A Journey Through Processing Flows of Data

Paper We Love ⋈ Kafka Meetup

Who I Am

Emanuele Della Valle
Professor @ Polimi
Inventor of Stream Reasoning
Kafka Enthusiast

Who I Am

Riccardo Tommasini
PhD Candidate @ Polimi
Thesis: Velocity on the Web
Future AssistantProfessor @
University of Tartu, Estonia
Enthusiast!

Timeline

Precision not Recall

2002 2005 2006 2007 2008 2010 2014 2015 2018

The Origin

Models and Issues in Data Stream Systems *

Brian Babcock Shivnath Babu Mayur Datar Rajeev Motwani Jennifer Widom

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Abstract

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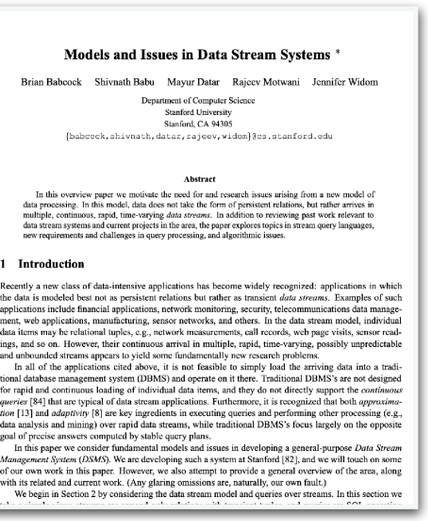

Models and Issues in Data Stream Systems *

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The 8 Requirements of Real-Time Stream Processing

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It's a Streaming World! Reasoning upon Rapidly Changing Information

MOA: Massive Online Analysis

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Dynamically Scaling

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Apache Samza

Apache Flink™: Stream and Batch Processing in a Single Engine

Abstract

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The Vision

The 8 Requirements of Real-Time Stream Processing

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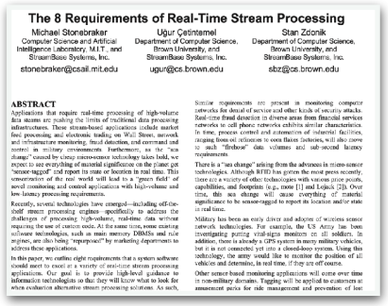

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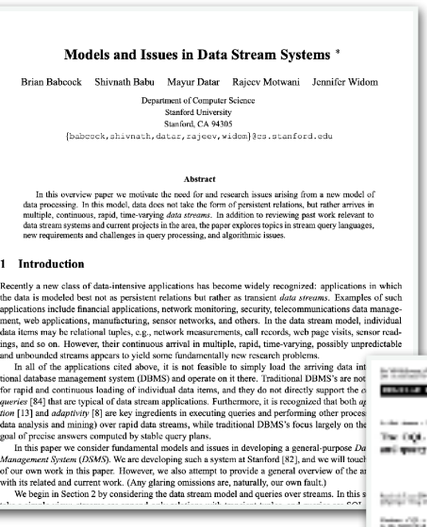

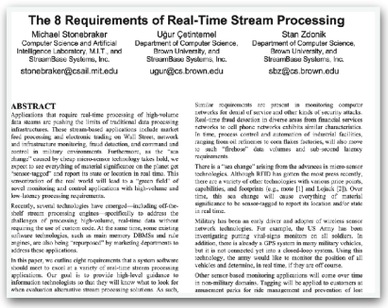

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The VLDB Journal (2006) 15(2): 121–142
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REGULAR PAPER

Arvind Arasu · Shivnath Babu · Jennifer Widom

The CQL continuous query language: semantic foundations and query execution

Received: 7 June 2004 / Accepted: 22 November 2004 / Published online: 22 July 2005

Abstract *CQL*, a *continuous query language*, is supported by the STREAM prototype data stream management system (DSMS) at Stanford. CQL is an expressive SQL-based declarative language for registering continuous queries against streams and stored relations. We begin by presenting an abstract semantics that relies only on "black-box" mappings among streams and relations. From these mappings we define a precise and general interpretation for continuous queries. CQL is an instantiation of our abstract semantics using SQL to map from relations to relations, window specifications derived from SQL-99 to map from streams to relations, and three new operators to map from relations to streams. Most of the CQL language is operational in the STREAM system. We present the structure of CQL's query execution plans as well as details of the most important components: operators, interoperator queues, synopses, and sharing of components among multiple operators and queries. Examples throughout the paper are drawn from the *Linear Road* benchmark recently proposed for DSMSs. We also curate a public repository of data stream applications that includes a wide variety of queries expressed in CQL. The relative ease of capturing these applications in CQL is [2, 19, 20, 23, 28, 32]. However, these queries tend to be simple and primarily for illustration – a precise language semantics, particularly for more complex queries, often is left unclear. Furthermore, very little has been published to date covering execution details of general-purpose continuous queries. In this paper we present the *CQL* language and execution engine for general-purpose continuous queries over streams and stored relations. CQL (for *continuous query language*) is an instantiation of a precise abstract continuous semantics also presented in this paper, and CQL is implemented in the *STREAM* prototype data stream management system (DSMS) at Stanford.[1]

It may appear initially that defining a continuous query language over (relational) streams is not difficult: take a relational query language, replace references to relations with references to streams, register the query with the stream processor, and wait for answers to arrive. For simple monotonic queries over complete stream histories, indeed this approach is nearly sufficient. However, as queries get more complex – when we add aggregation, subqueries, windowing constructs, relations mixed with streams, etc. – the situation becomes much murkier. Consider the following simple query:

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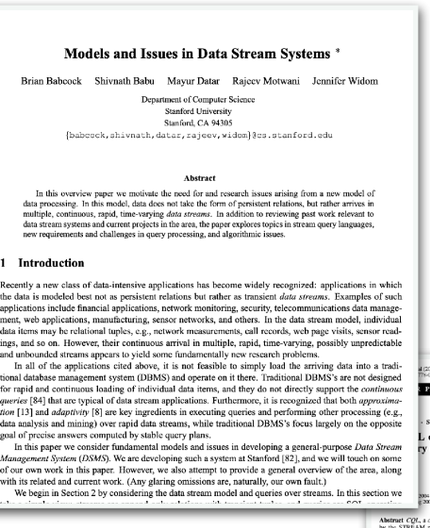

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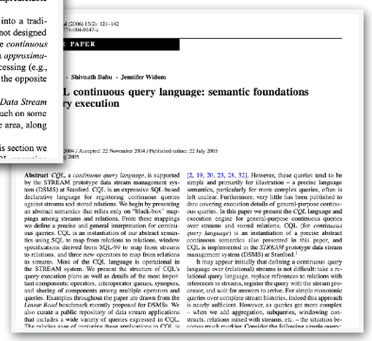

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Albert Bifet
Geoff Holmes
Richard Kirkby
Bernhard Pfahringer
Department of Computer Science
University of Waikato
Hamilton, New Zealand

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Abstract

Massive Online Analysis (MOA) is a software environment for implementing algorithms and running experiments for online learning from evolving data streams. MOA includes a collection of offline and online methods as well as tools for evaluation. In particular, it implements boosting, bagging, and Hoeffding Trees, all with and without Naive Bayes classifiers at the leaves. MOA supports bi-directional interaction with WEKA, the Waikato Environment for Knowledge Analysis, which is an award-winning open-source workbench containing implementations of a wide range of batch machine learning methods.

A data stream environment has different requirements from the traditional batch learning setting. The most significant are the following:

Requirement 1 Process an example at a time, and inspect it only once (at most)

Requirement 2 Use a limited amount of memory

Dynamically Scaling
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Apache Samza

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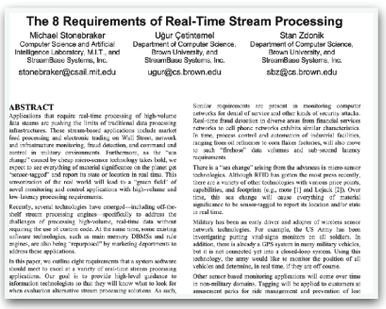

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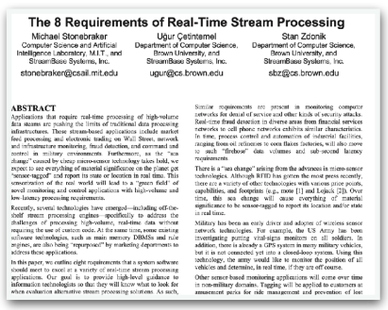

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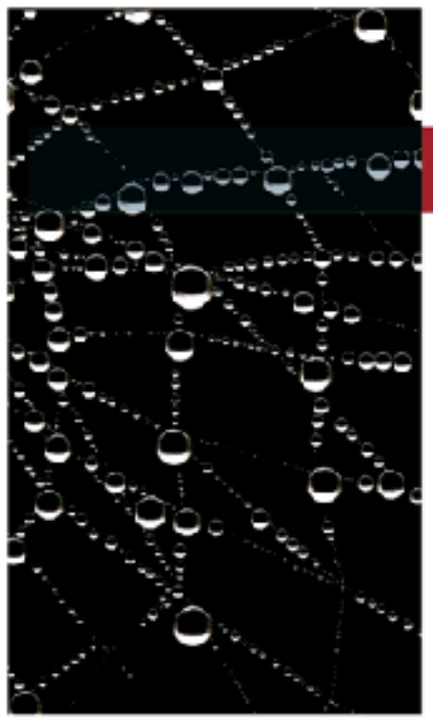

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Editor: **Steffen Staab,** University of Koblenz-Landau, staab@uni-koblenz.de

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Frank van Harmelen, *Vrije Universiteit Amsterdam*
Dieter Fensel, *University of Innsbruck*

Will there be a traffic jam on this highway? Can we reroute travelers on the basis of the forecast? By examining the clickstream from a given IP, can we discover shifts in interest of the person behind the computer? Which content on the news Web portal is attracting the most attention? Which navigation pattern would lead readers to other news related to that content? Do trends in medical records indicate any new disease spreading in a given part of the world? Where are all my

The state of the art in reasoning over changing worlds is based on temporal logic and belief revision; these are heavyweight tools, suitable for data that changes in low volumes at low frequency. Similarly, the problem of changing vocabularies and evolving ontologies has undergone thorough investigation, but here the standard practice relies on configuration management techniques taken from software engineering, such as vocabulary and ontology versioning. These are suitable for ontologies that change on a weekly or monthly basis, but not

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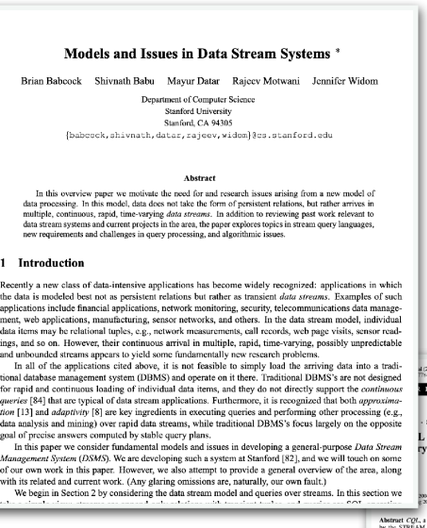

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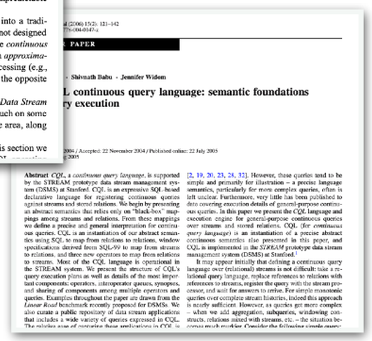

PAPER

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MOA: Massive Online Analysis

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{takidau, slava, chambers, chernyak, rfernand, relax, sgmc, millsd, fjp, eschmidt, samuelw}@google.com

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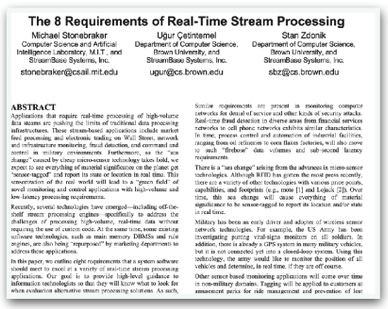

The 8 Requirements of Real-Time Stream Processing

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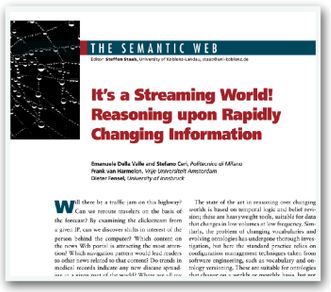

THE SEMANTIC WEB

Editor: Steffen Staab, University of Koblenz-Landau, staab@uni-koblenz.de

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Apache Flink[TM]: Stream and Batch Processing in a Single Engine

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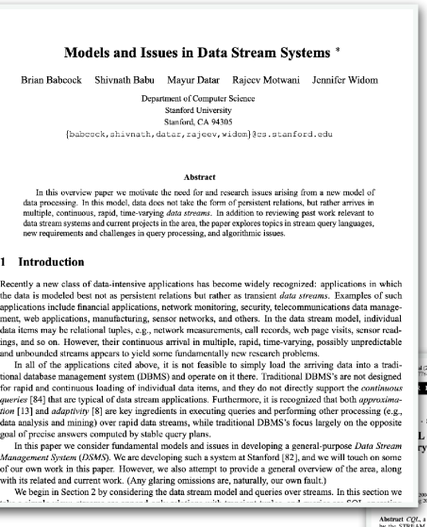
Models and Issues in Data Stream Systems *

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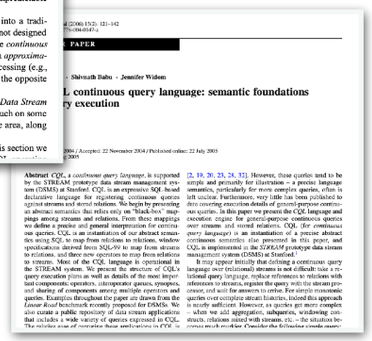
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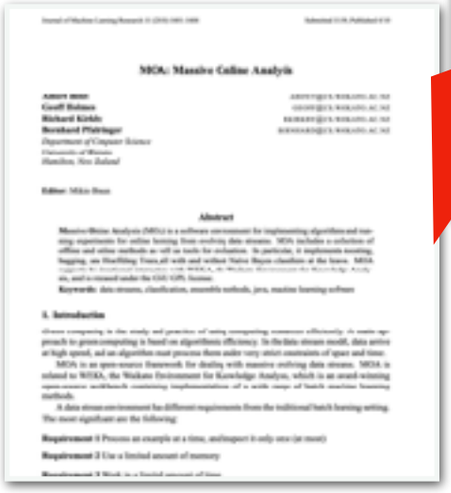
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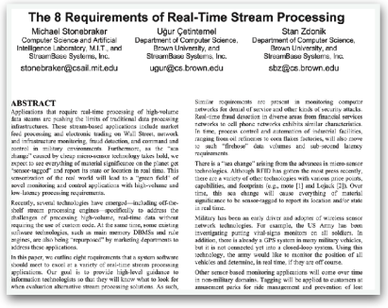
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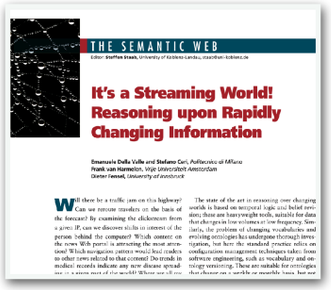
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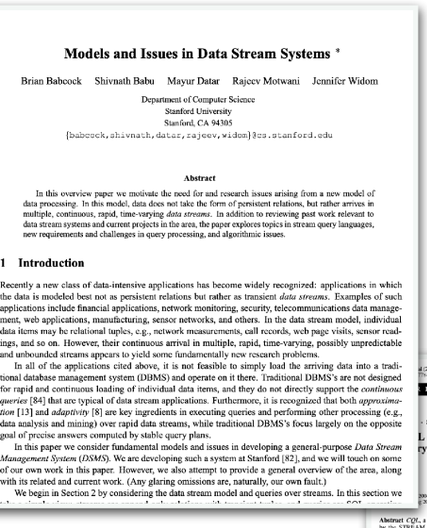

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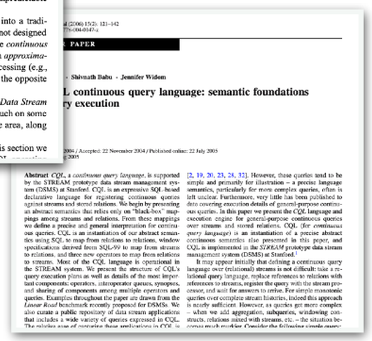

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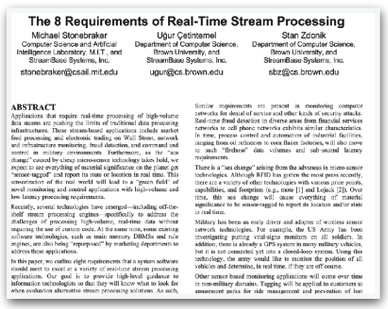

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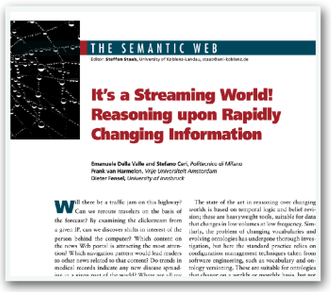

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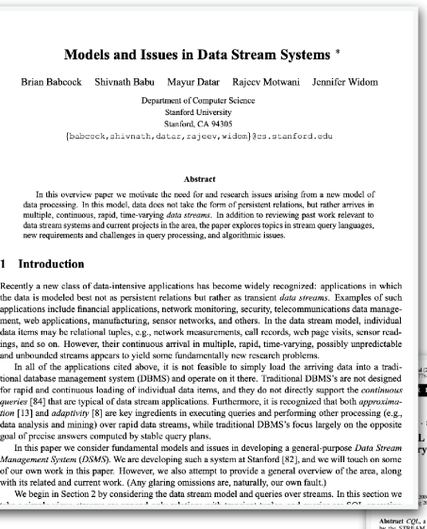
1. Introduction

Green computing is the study and practice of using computing resources efficiently. A main approach to green computing is based on algorithmic efficiency. In the data stream model, data arrive at high speed, and an algorithm must process them under very strict constraints of space and time.

MOA is an open-source framework for dealing with massive evolving data streams. MOA is related to WEKA, the Waikato Environment for Knowledge Analysis, which is an award-winning open-source workbench containing implementations of a wide range of batch machine learning

Timeline

Precision not Recall


Models and Issues in Data Stream Systems *

Brian Babcock Shivnath Babu Mayur Datar Rajeev Motwani Jennifer Widom

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Abstract

In this overview paper we motivate the need for and research issues arising from a new model of data processing. In this model, data does not take the form of persistent relations, but rather arrives in multiple, continuous, rapid, time-varying *data streams*. In addition to reviewing past work relevant to data stream systems and current projects in the area, the paper explores topics in stream query languages, new requirements and challenges in query processing, and algorithmic issues.

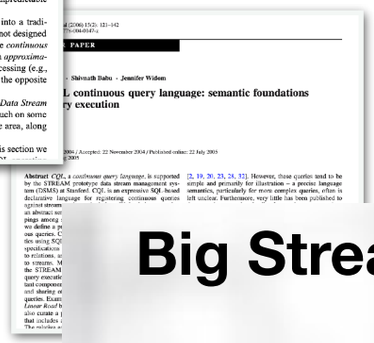
1 Introduction

Recently a new class of data-intensive applications has become widely recognized: applications in which the data is modeled best not as persistent relations but rather as transient *data streams*. Examples of such applications include financial applications, network monitoring, security, telecommunications data management, web applications, manufacturing, sensor networks, and others. In the data stream model, individual data items may be relational tuples, e.g., network measurements, call records, web page visits, sensor readings, and so on. However, their continuous arrival in multiple, rapid, time-varying, possibly unpredictable and unbounded streams appears to yield some fundamentally new research problems.

In all of the applications cited above, it is not feasible to simply load the arriving data into a traditional database management system (DBMS) and operate on it there. Traditional DBMS's are not designed for rapid and continuous loading of individual data items, and they do not directly support the *continuous queries* [84] that are typical of data stream applications. Furthermore, it is recognized that both *approximation* [13] and *adaptivity* [8] are key ingredients in executing queries and performing other processing (e.g., data analysis and mining) over rapid data streams, while traditional DBMS's focus largely on the opposite goal of precise answers computed by stable query plans.

In this paper we consider fundamental models and issues in developing a general-purpose *Data Stream Management System (DSMS)*. We are developing such a system at Stanford [82], and we will touch on some of our own work in this paper. However, we also attempt to provide a general overview of the area, along with its related and current work. (Any glaring omissions are, naturally, our own fault.)

We begin in Section 2 by considering the data stream model and queries over streams. In this section we


PAPER

Shivnath Babu · Jennifer Widom

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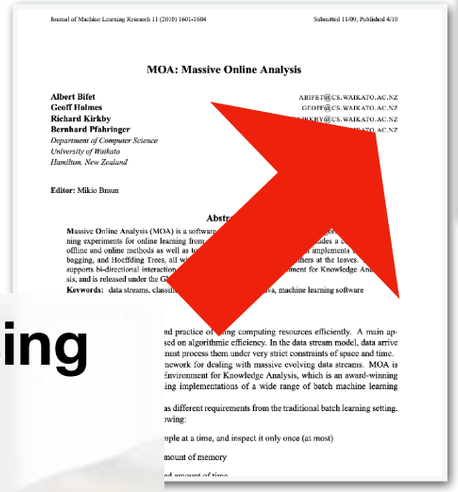
Journal of Machine Learning Research 11 (2010) 1601-1604 Submitted 11/09; Published 4/10

MOA: Massive Online Analysis

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Geoff Holmes GEOFF@CS.WAIKATO.AC.NZ
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Editor: Mikio Braun

Abstract

Massive Online Analysis (MOA) is a software
ning experiments for online learning from
offline and online methods as well as to
bagging, and Hoeffding Trees, all w
supports bi-directional interaction
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Keywords: data streams, classifi
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Dynamically Scaling
of

The Dataflow Model: A Practical Approach to Balancing Correctness, Latency, and Cost in Massive-Scale, Unbounded, Out-of-Order Data Processing

ABSTRACT

1. INTRODUCTION

Apache Samza


ables: Two Sides of th

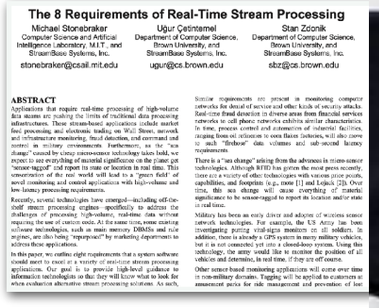

Apache Flink™: Stream and Batch Processing in a Single Engine

Abstract

1 Introduction


Structured Streaming: A Declarative API for Real-Time Applications in Apache Spark


Big Stream Processing Starts


The 8 Requirements of Real-Time Stream Processing

Michael Stonebraker
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ABSTRACT

2002 2005 2006 2007 2008 2010 2014 2015 2018

Timeline

Models and Issues in Data Stream Systems *

The CQL continuous query language: semantic foundations and query execution

The 8 Requirements of Real-Time Stream Processing

NiagaraCQ: A Scalable Continuous Query System for Internet Databases.

Aurora: A New Model and Architecture for Data Stream Management

TelegraphCQ: Continuous Dataflow Processing.

It's a Streaming World! Reasoning upon Rapidly Changing Information

MOA: Massive Online Analysis

Apache Samza

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S. Murthy et al. Pulsar – Real-Time Analytics at Scale. Technical report, eBay, 2015.

Summingbird: A Framework for Integrating Batch and Online MapReduce Computations.

Trill: A High-Performance Incremental Query Processor for Diverse Analytics.

2002 2005 2006 2007 2008 2010 2014 2015 2018

Our Focus

Streams and Tables: Two Sides of the Same Coin

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TRACT

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Defining semantics for stream processing, however

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Arvind Arasu · Shivnath Babu · Jennifer Widom

The CQL continuous query language: semantic foundations and query execution

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It may appear initially that defining a continuous query language over (relational) streams is not difficult: take a relational query language, replace references to relations with references to streams, register the query with the stream processor, and wait for answers to arrive. For simple monotonic

Is this too ambitious?

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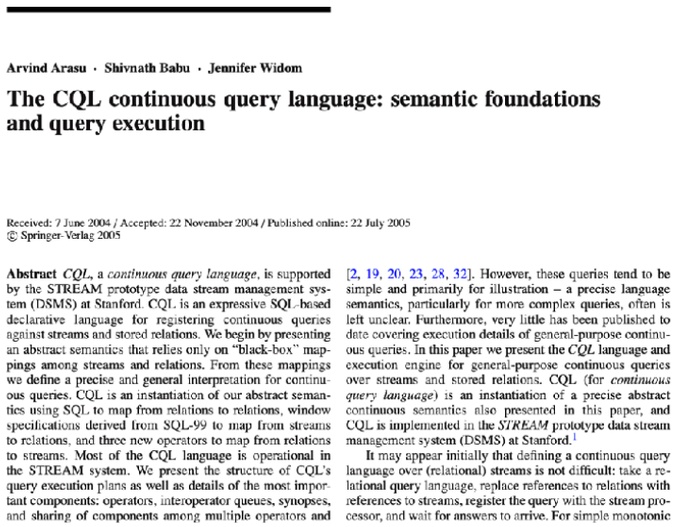

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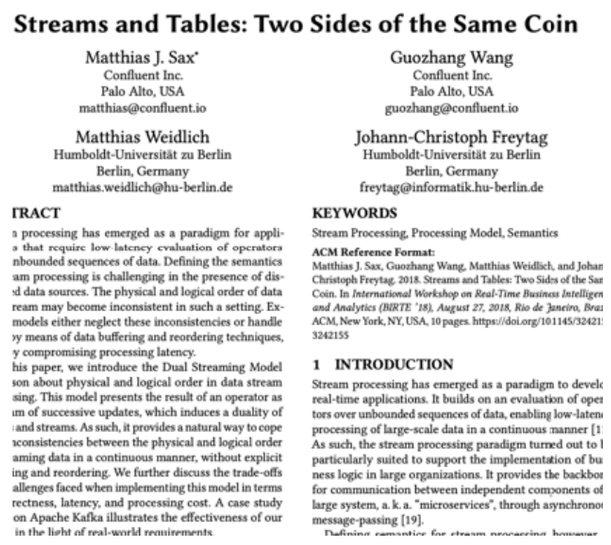
A (Query) Language Perspective

It addresses the problem of manipulating and managing data-streams**.** It stresses on the **operations** that are **necessary** to build **applications.** Some **Assumptions** are made on the underlying **system**(s)**.**

A ~~new~~ hybrid ~~hope~~ perspective

It addresses the problems in between. How do we map the abstraction of an high-level language to the underlying system?



Streams and Tables: Two Sides of the Same Coin

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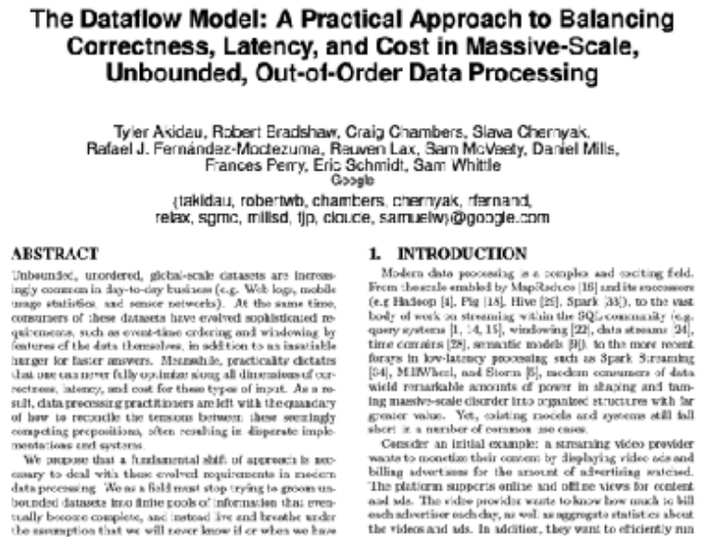

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A System Perspective

It address the problem of dealing with **unbounded data.** Discuss the systems' **primitives** that are necessary to guarantee **low-latency** and **fault-tolerance in** presence of *uncertainty*, e.g., late arrivals.

Goals

CQL

- Exploit lesson learnt in RDBMS theory.
- simple, clear, yet powerful language.
- efficiently combine streams and relations.

DSM

- low-latency is paramount.
- take data distribution and ordering into account.
- avoid implicit operator semantics.

DFM

- Correctness first with sessions support.
- Latency requirements vs resource cost should dictate system choice.
- Single processing model for bounded and unbounded data.

Time

CQL

- DSMS Clock Time, i.e., the timestamp assigned by the DSMS.
- Source Time, i.e., the timestamp assigned by the source.
- Source Heartbeat are used to declare no element with lower timestamp will be sent.

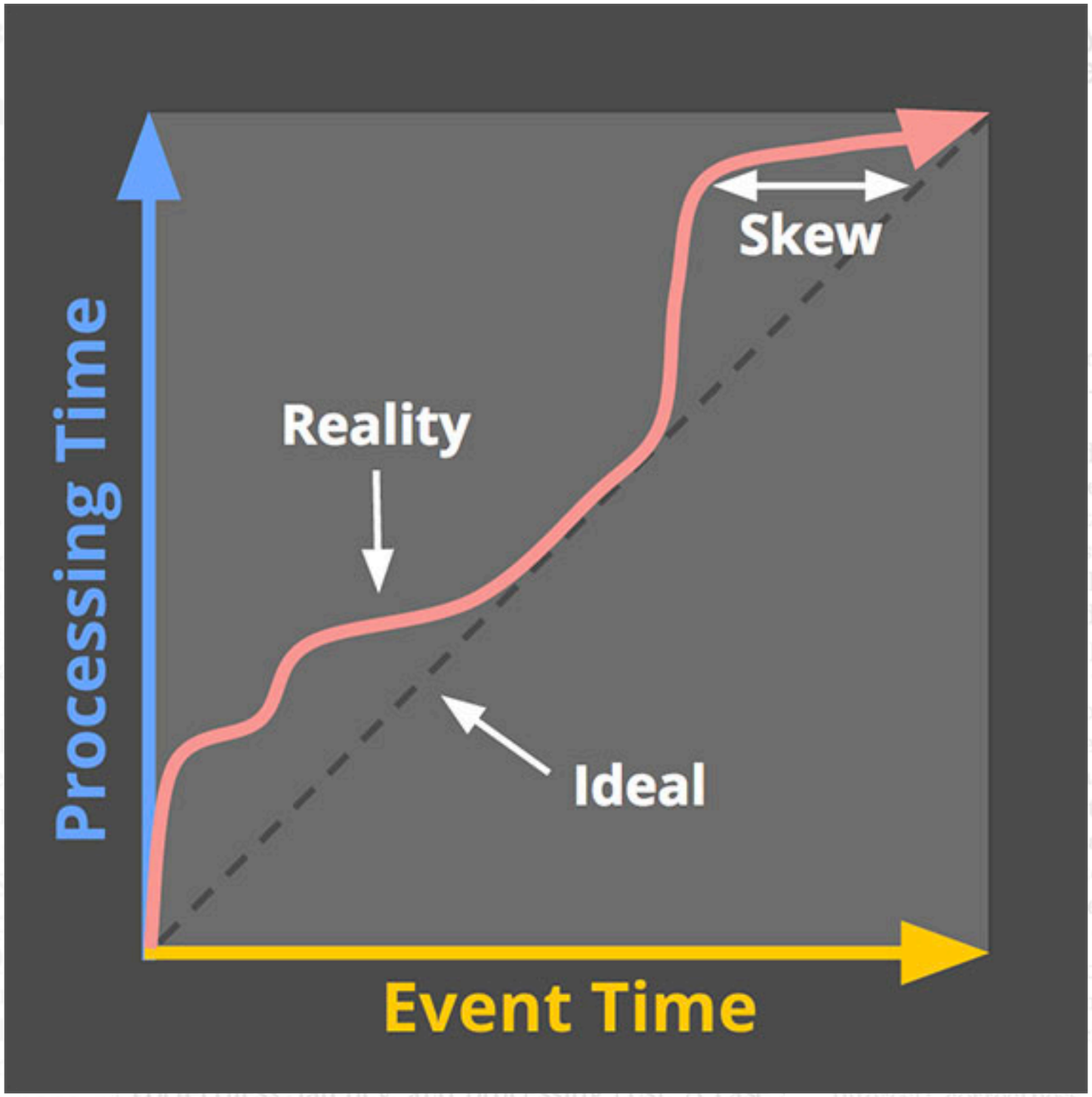
DSM

- Logical Order induced by the timestamp assigned by the data source.
- Physical Order induced by the timestamp assigned by the system at ingestion.

DFM

- Event Time is the time at which the event itself actually *occurred.*
- Processing Time is the time at which an event is *observed* during *processing.*
- Watermark, i.e., global **progress metrics** that tracks the skewness between ET and PT.

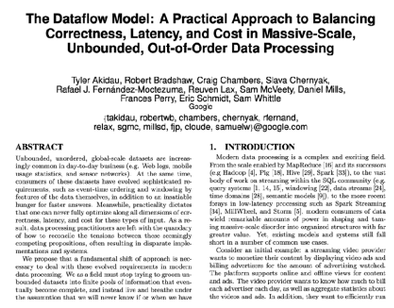
Watermark



Abstractions

CQL	DSM	DFM
• Streams • (Time-Varying) Relations*	• Change-log Streams • Records Streams • Tables	• PCollections (bounded and unbounded)

CQL in 3 Slides



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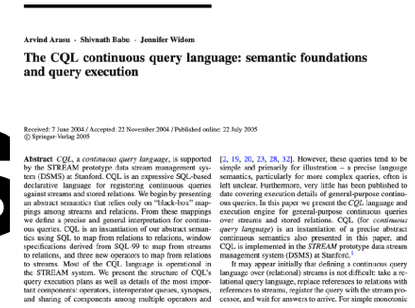
A Stream ***S*** *is a possibly infinite* ***multi-set*** *of elements <s,t> where s is a tuple belonging to the schema of S and t is a timestamp.*

Relation ***R*** is a set of tuples $(d_1, d_2, ..., d_n)$, where each element d_j is a member of D_j, a data domain[1].

[1] *a Data Domain refers to all the values which a data element may contain.*

CQL in ~~3~~ 4 Slides



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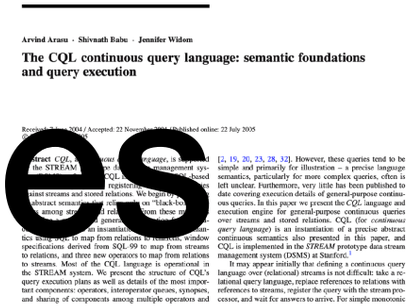
A Stream ***S*** *is a possibly infinite* ***multi-set*** *of elements <s,t> where s is a tuple belonging to the schema of S and t is a timestamp.*

~~*Relation* ***R*** is a set of tuples $(d_1, d_2, ..., d_n)$, where each element d_j is a member of D_j, a data domain[1].~~

[1] *a Data Domain refers to all the values which a data element may contain.*

Ok, CQL in ~~4~~ 5 Slides



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Relation ***R*** is a mapping from each time instant in T to a **finite** but **unbounded bag** of tuples belonging to the **schema** of **R**.

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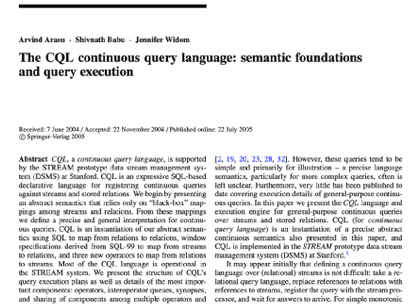

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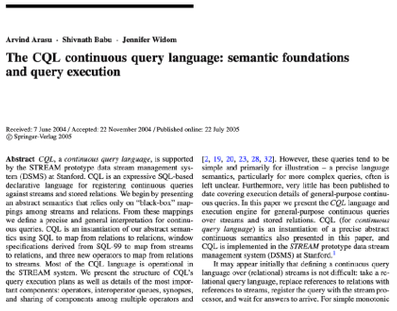

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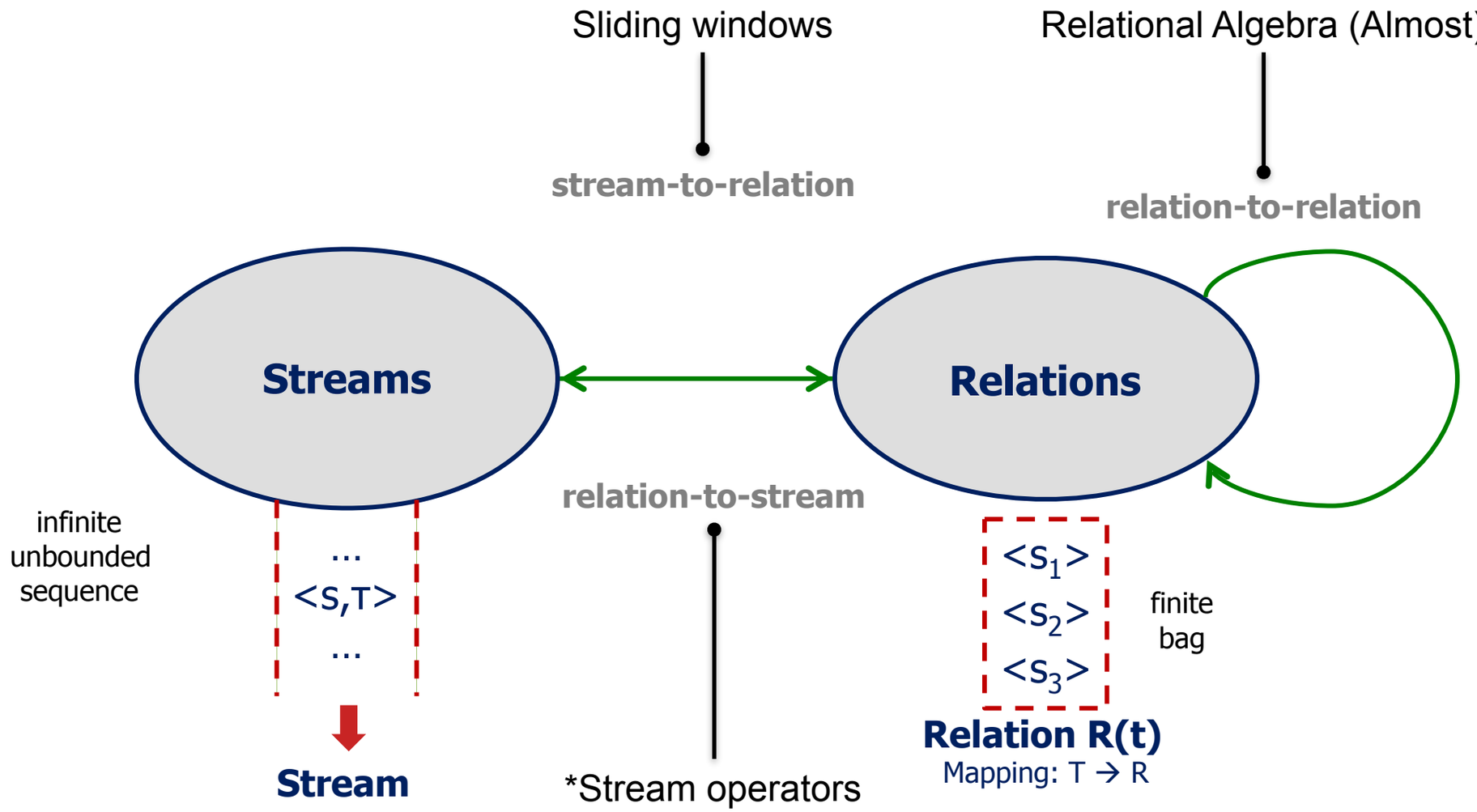
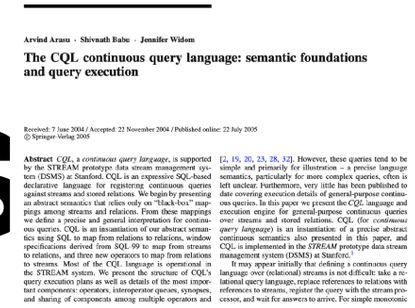


CQL in ~~5~~ 6 Slides



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Stream-to-Relation Operators:

- **Sliding Window**:
  FROM S [RANGE 5 Minutes]

- **Parametric Sliding Windows:**
  FROM S [RANGE 5 Minutes Slide 1 Min]

- **Partitioned Windows**:
  FROM S [PARTITIONED BY $A_1..A_n$ ROW m]

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CQL in 6 Slides

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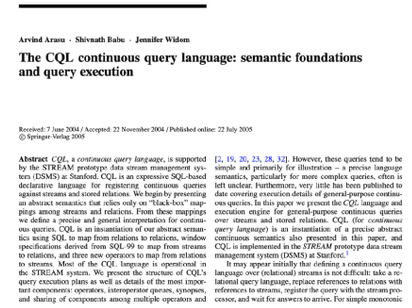

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Relation-to-Stream Operators:

- **Rstream**: streams out all data in the last step
- **Istream**: streams out data in the last step that wasn’t on the previous step, i.e. streams out what is new
- **Dstream**: streams out data in the previous step that isn’t in the last step, i.e. streams out what is old

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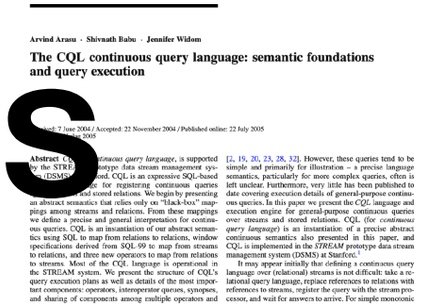
DFM in X<42* Slides

Reasoning about time



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- **What** results are being computed
- **Where** in event time are being computed
- **When** in processing time are being materialised
- **How** “earlier results” relate to “later refinements”

*overestimation

DFM in X Slides

(WHAT) Processing Model

A Stream is represented as a possibly unbounded collection of key-value pairs, i.e., a PCollection<K,V>.

PTransforms are PCollections-to-PCollections operations.

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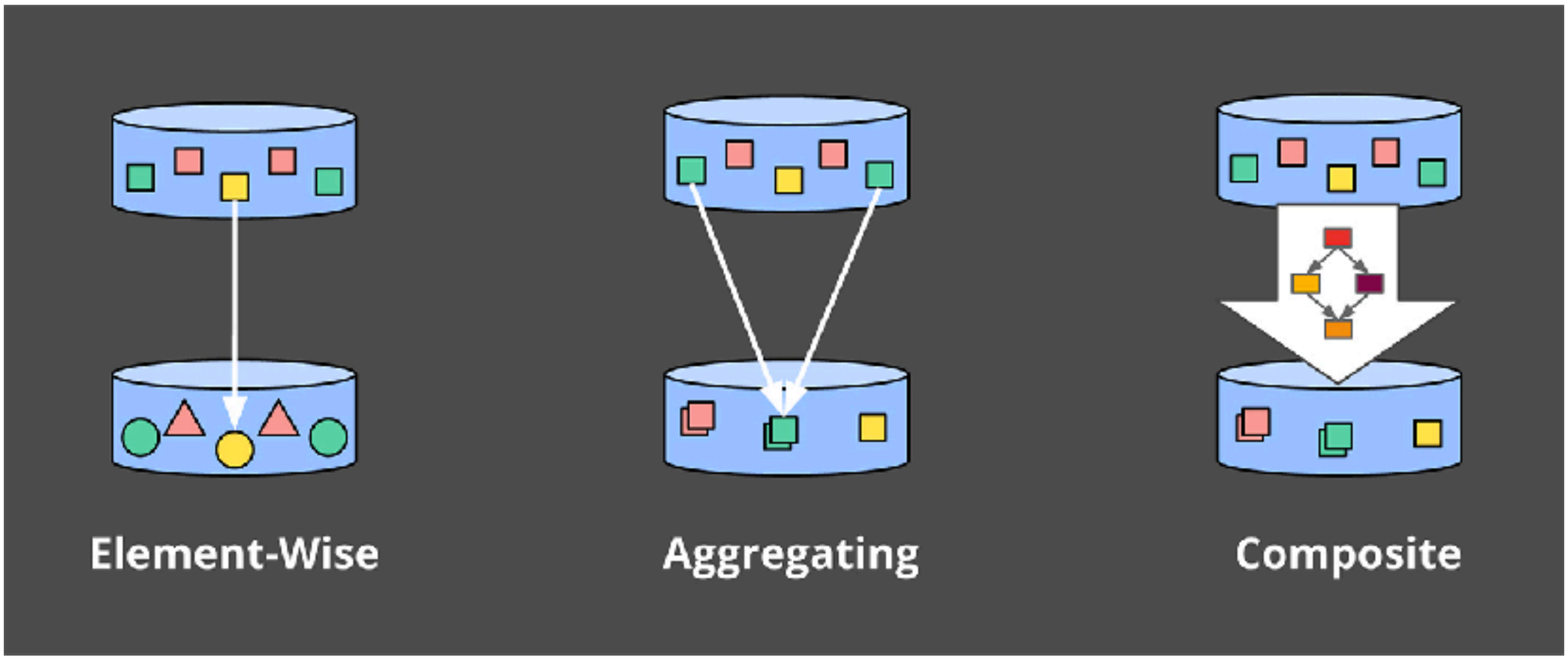

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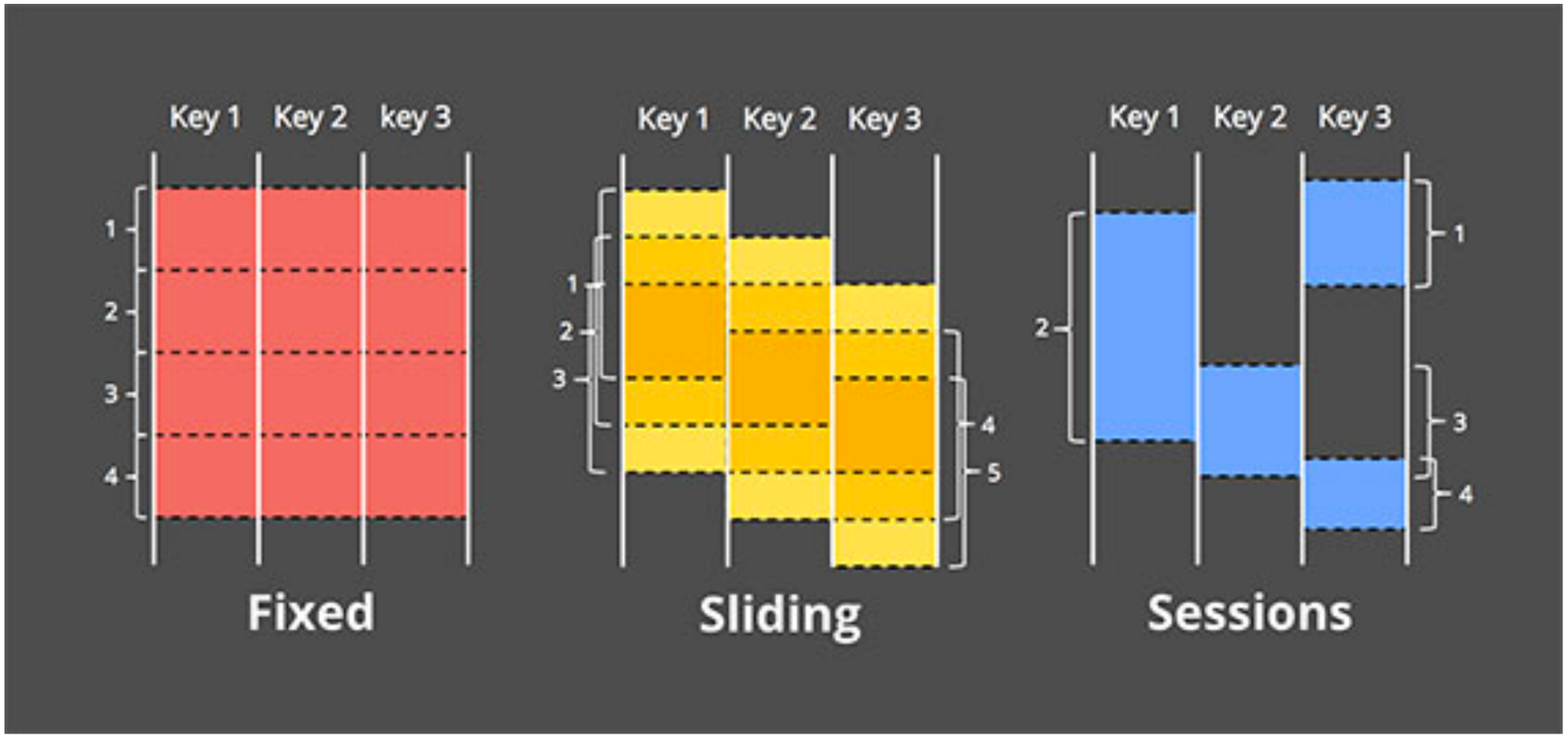

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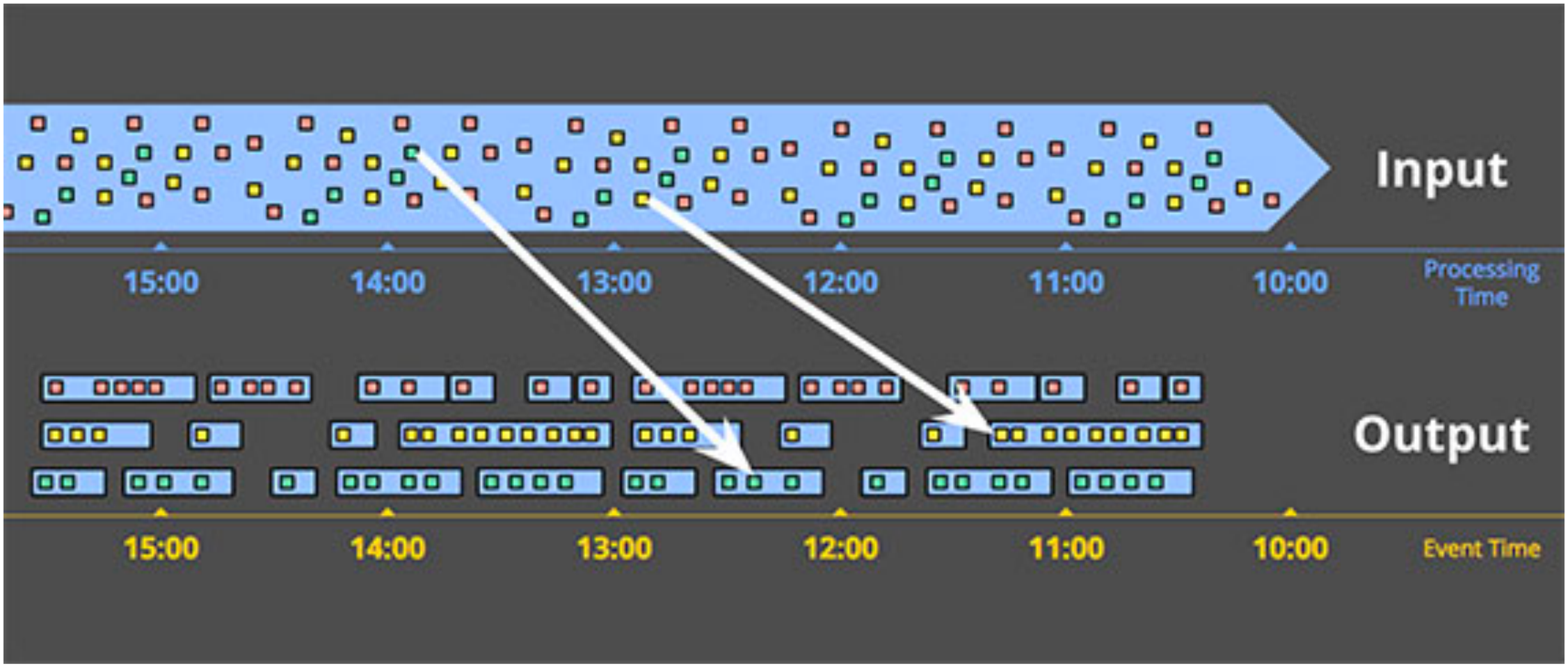

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Wall of Text

Disclaimer

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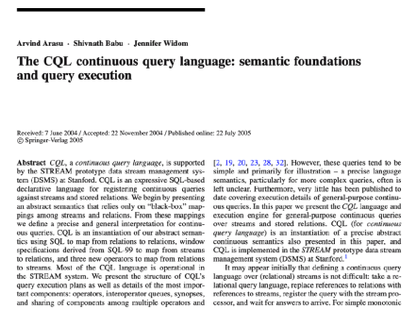

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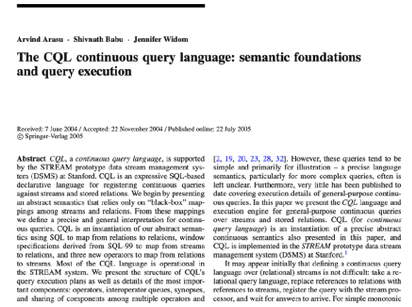
- The DFM windowing model requires extended primitives than CQL's one.
- Window Assignment, i.e., each element is assigned to a corresponding window.
- Window Merge:
  - **Drop Timestamp: only the window interval is relevant here on**
  - GroupBy Key: to enable parallel execution
  - Window Merge (the merge logic depends on the window strategy)
  - GroupByWindow: to ensure elements are processed in sequence window-wise.
- ExpandToElements: assigned a valid timestamp to the elements.

DFM in X Slides

(WHEN) Triggering Model



Arvind Arasu · Shivnath Babu · Jennifer Widom

The CQL continuous query language: semantic foundations and query execution

Received: 7 June 2004 / Accepted: 22 November 2004 / Published online: 22 July 2005
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Abstract *CQL*, a *continuous query language*, is supported by the STREAM prototype data stream management system (DSMS) at Stanford. CQL is an expressive SQL-based declarative language for registering continuous queries against streams and stored relations. We begin by presenting an abstract semantics that relies only on "black-box" mappings among streams and relations. From these mappings we define a precise and general interpretation for continuous queries. CQL is an instantiation of our abstract semantics using SQL to map from relations to relations, window specifications derived from SQL-99 to map from streams to relations, and three new operators to map from relations to streams. Most of the CQL language is operational in the STREAM system. We present the structure of CQL's query execution plans as well as details of the most important components: operators, interoperator queues, synopses, and sharing of components among multiple operators and [2, 19, 20, 23, 28, 32]. However, these queries tend to be simple and primarily for illustration – a precise language semantics, particularly for more complex queries, often is left unclear. Furthermore, very little has been published to date covering execution details of general-purpose continuous queries. In this paper we present the CQL language and execution engine for general-purpose continuous queries over streams and stored relations. CQL (for *continuous query language*) is an instantiation of a precise abstract continuous semantics also presented in this paper, and CQL is implemented in the *STREAM* prototype data stream management system (DSMS) at Stanford.[1]

It may appear initially that defining a continuous query language over (relational) streams is not difficult: take a relational query language, replace references to relations with references to streams, register the query with the stream processor, and wait for answers to arrive. For simple monotonic

- In order to build unaligned (apply across subset of the data) event-time windows DFM is forced to decouple the reporting of the window content.

- To do so, DFM introduces an orthogonal model that allows to signal when a window is ready to be processed.

DFM in X Slides

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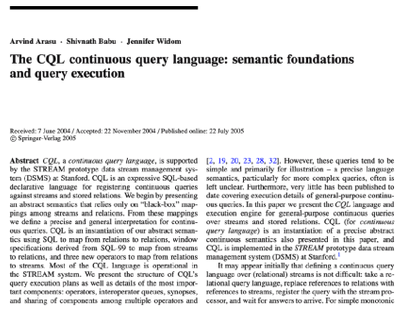

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- To do so, DFM introduces an orthogonal model that allows to signal when a window is ready to be processed.

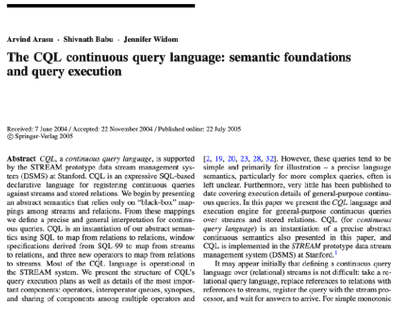
- Triggers solve this issue allowing DFM users to write an arbitrary logic to signal the completion of a window.

Wall of Text

Disclaimer

DFM in X Slides

(HOW) Triggering Model (part 2)



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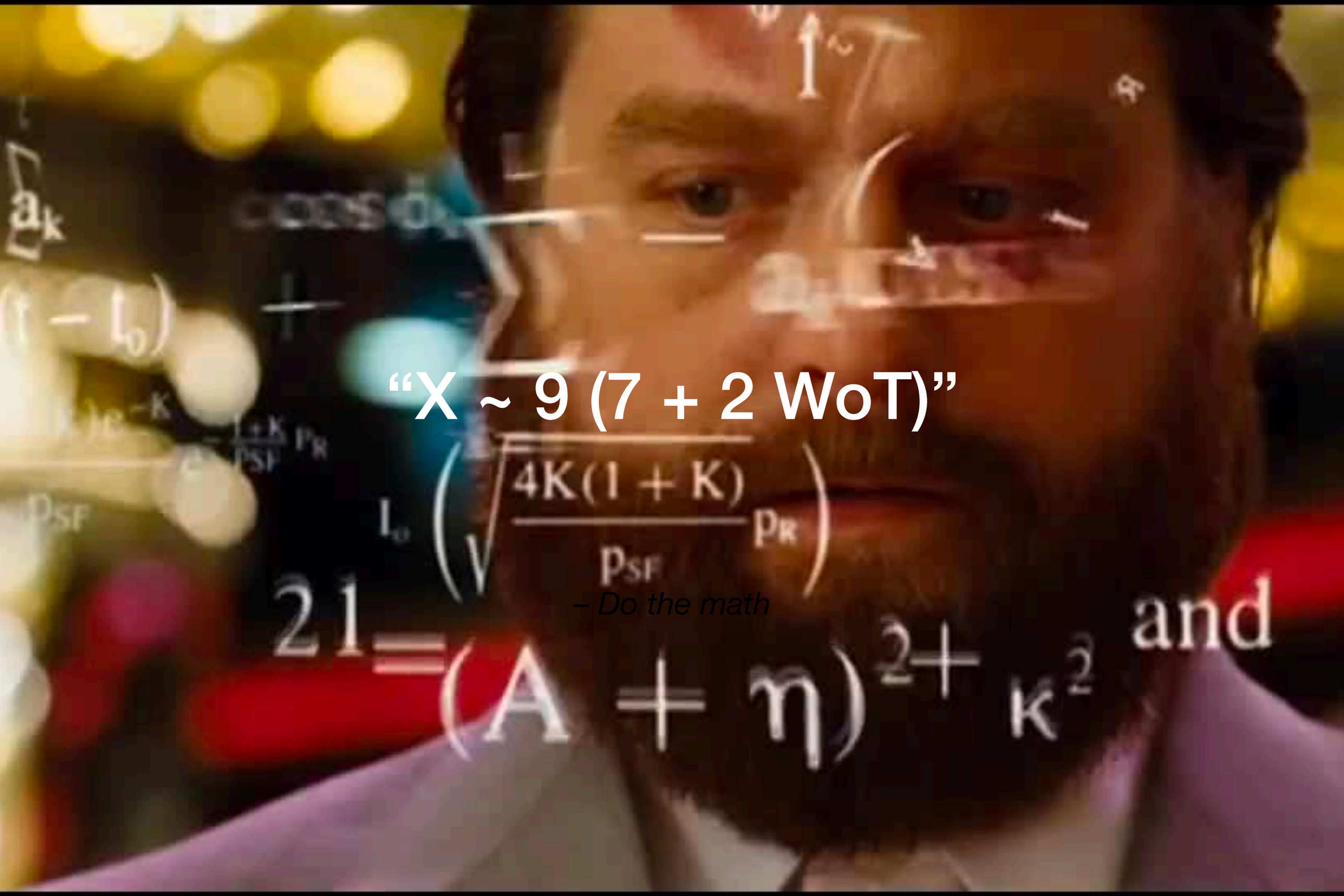
In addition to the triggering semantics, DFM introduces different refinements models to deal with late arrivals

- Discarding, i.e., upon triggering, window contents are discarded and later results bear no relation to previous results.

- Accumulating, i.e., upon triggering, window contents are left intact in a persistent state and later results will become a refinement to previous results

- Accumulating & Retracting, i.e, it extends the accumulating semantics with retraction of the previous value.


"X ~ 9 (7 + 2 WoT)"
– Do the math
$$21 = \left(\sqrt{\frac{4K(1+K)}{P_{SF}} P_R}\right) \text{ and } (A+\eta)^2 + \kappa^2$$

Was this too ambitious?

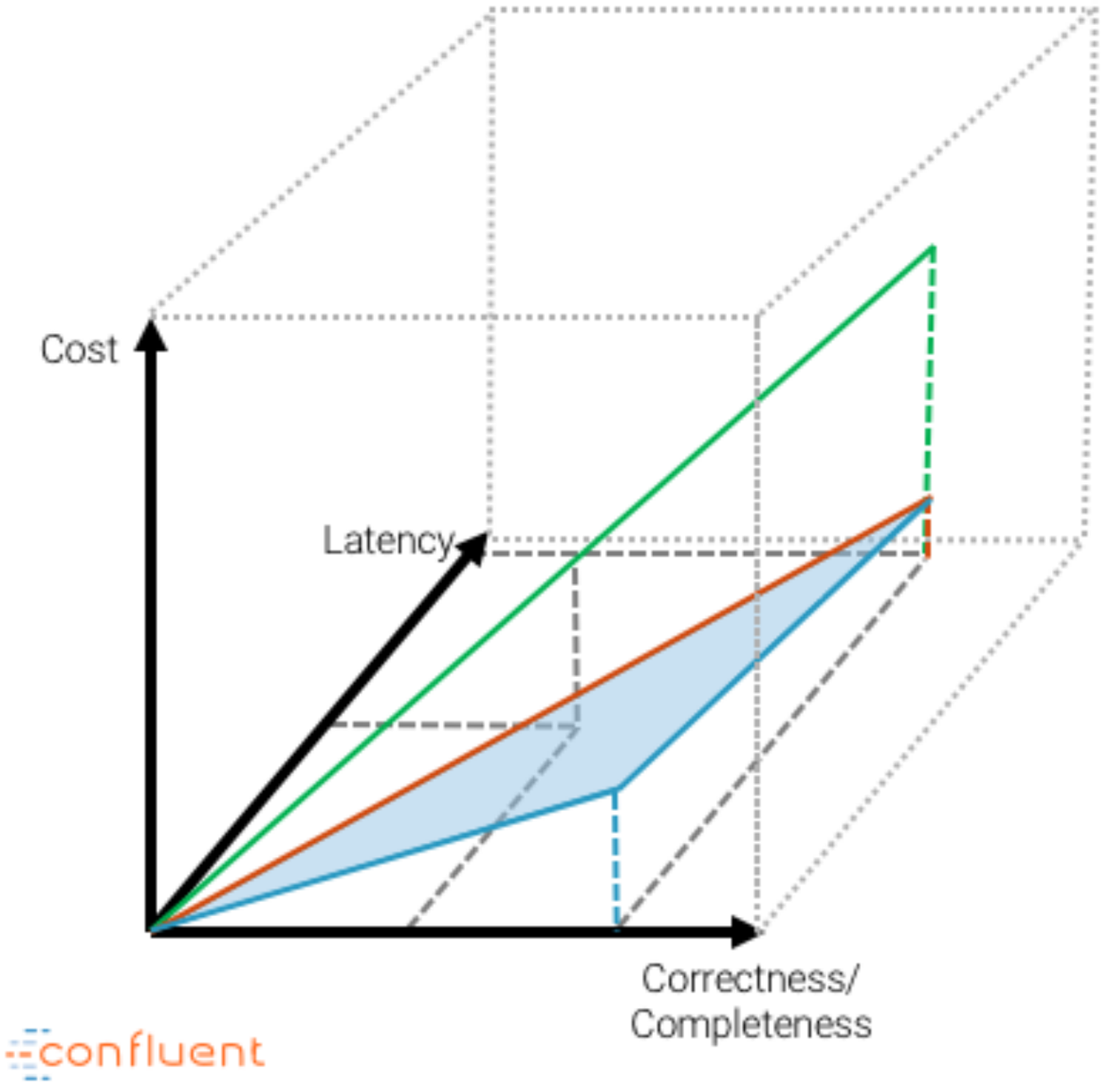
https://www.google.com/url?sa=i&source=images&cd=&ved=2ahUKEwjaouS-uK3mAhVEqaQKHfdOA4MQjRx6BAgBEAQ&url=https%3A%2F%2Fmedium.com%2Fpersonal-growth-lab%2Fshould-you-set-realistic-or-highly-ambitious-goals-7cf400505444&psig=AOvVaw3xPkWzwvy8SBXD9NS0o_Oe&ust=1576148163494865

ZZZZ


I'M NOT DONE

Dual Stream Model

The design space



Buffering and Reordering
- Ref: CQL[1], Trill[2]

Punctuations/Watermarks
- Ref: Li et al.[3], Krishnamurthy et al.[4]

Dual Streaming Model
- Continuous updates/changelogs
- Decouple latency from correctness
- Trade-off latency and cost
- Trade-off cost and completeness (retention time)

confluent

Streams and Tables: Two Sides of the Same Coin

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TRACT
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KEYWORDS
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As such, the stream processing paradigm turned out to
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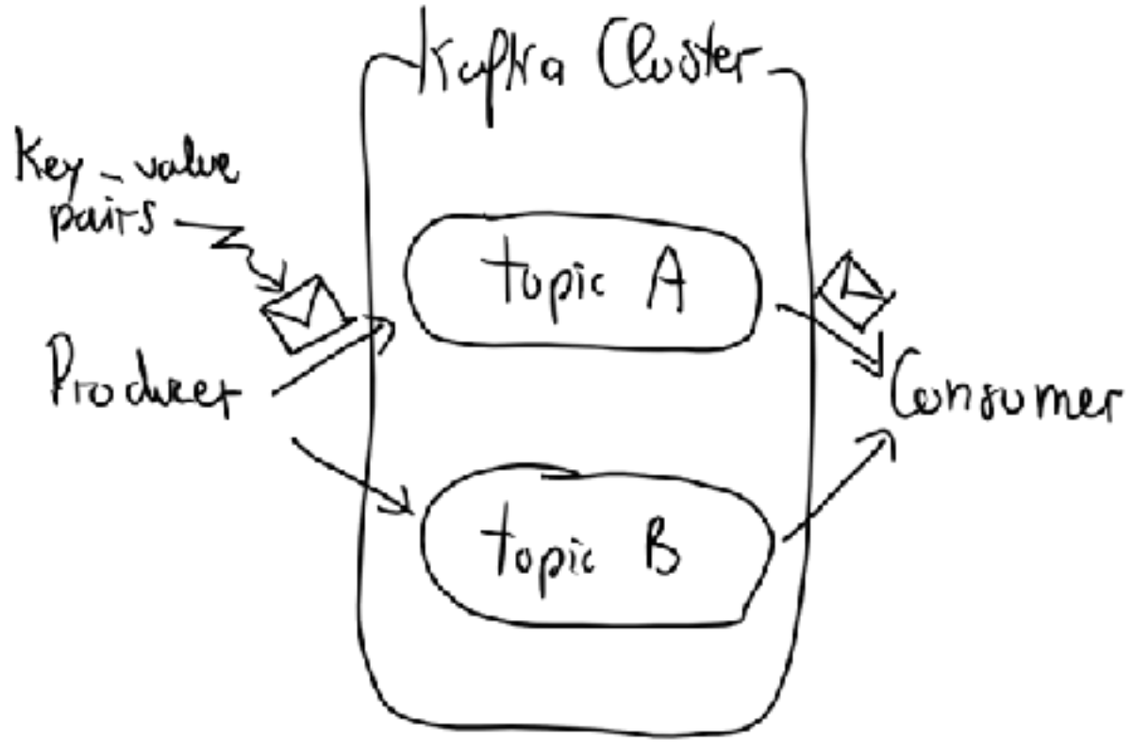
for communication between independent components o
asynchrono

Should I Take a Step back?

A Conceptual View of Kafka

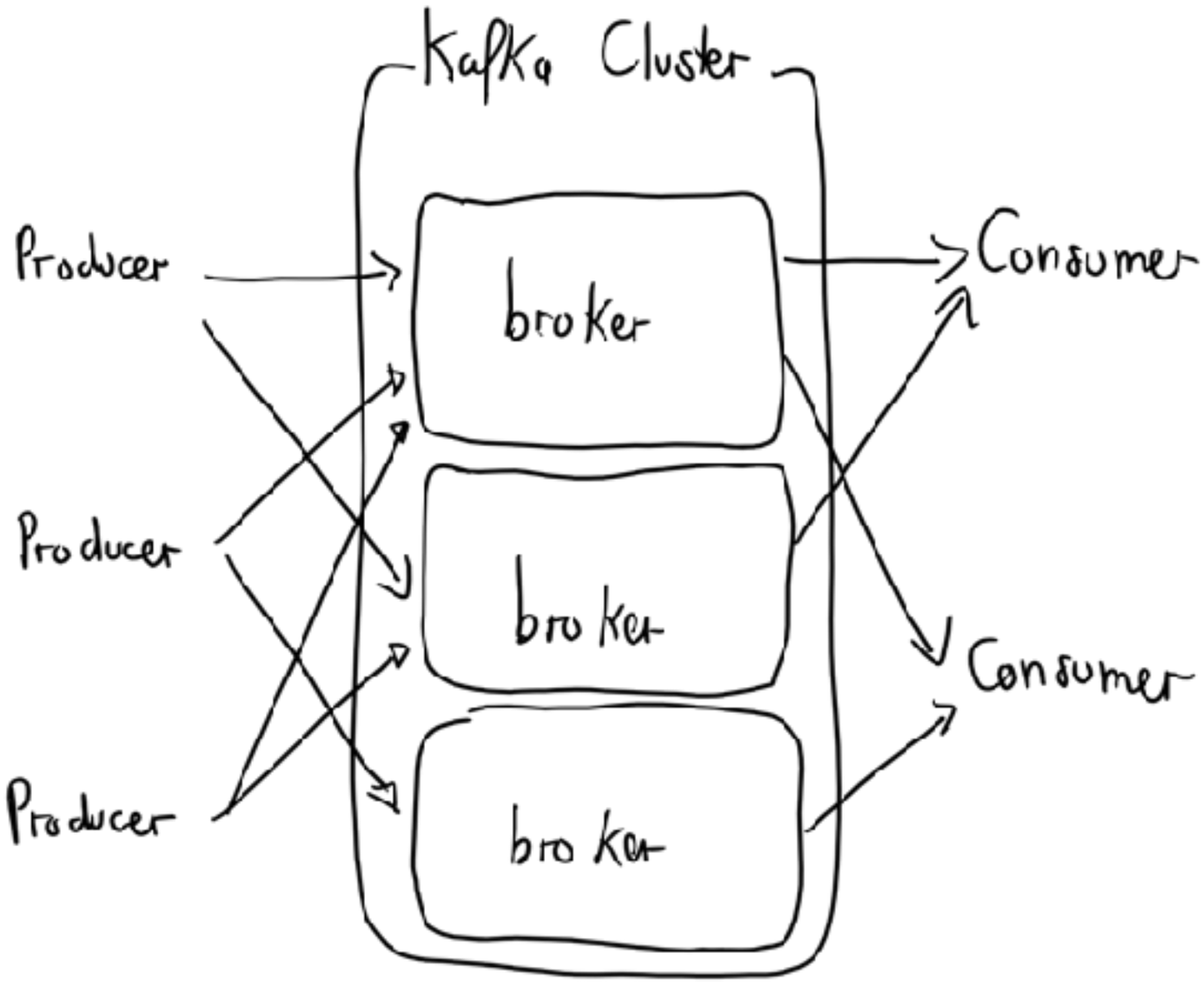
- **Producers** send messages on topics
- **Consumers** read messages from topics
- **Messages** are key-value pairs
- **Topics** are streams of messages
- Kafka cluster manages topics



curtesy of Emanuele Della Valle - http://emanueledellavalle.org

A Logical View of Kafka

- **Brokers** are the main storage and messaging components of the Kafka cluster



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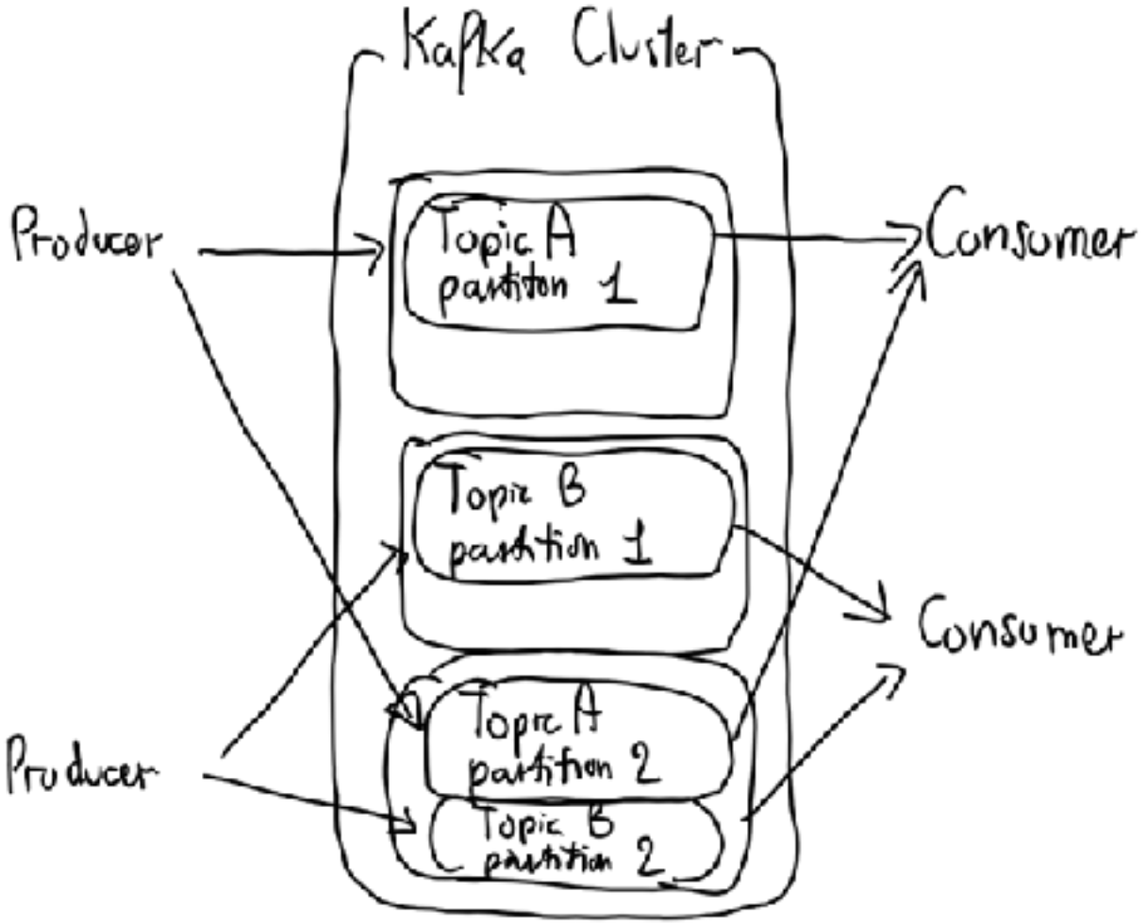
Reconciling the two views of Kafka

- Topics are partitioned across brokers
- Producers shard messages over the partitions of a certain topic
- Typically, the message key determines which Partition a message is assigned to



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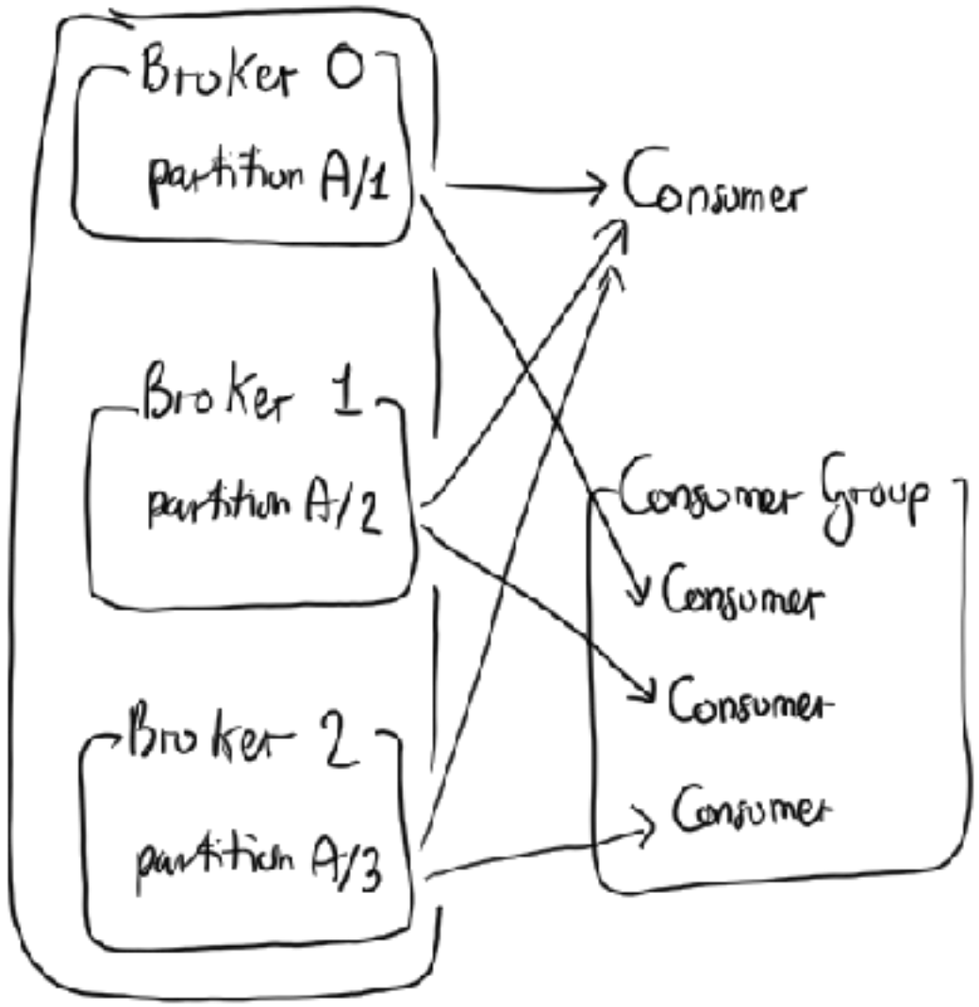
Topic partitioning invites distributed consumption

- Different Consumers can read data from the same Topic
  - By default, each Consumer will receive all the messages in the Topic
- Multiple Consumers can be combined into a Consumer Group
  - Consumer Groups provide scaling capabilities
  - Each Consumer is assigned a subset of Partitions for consumption



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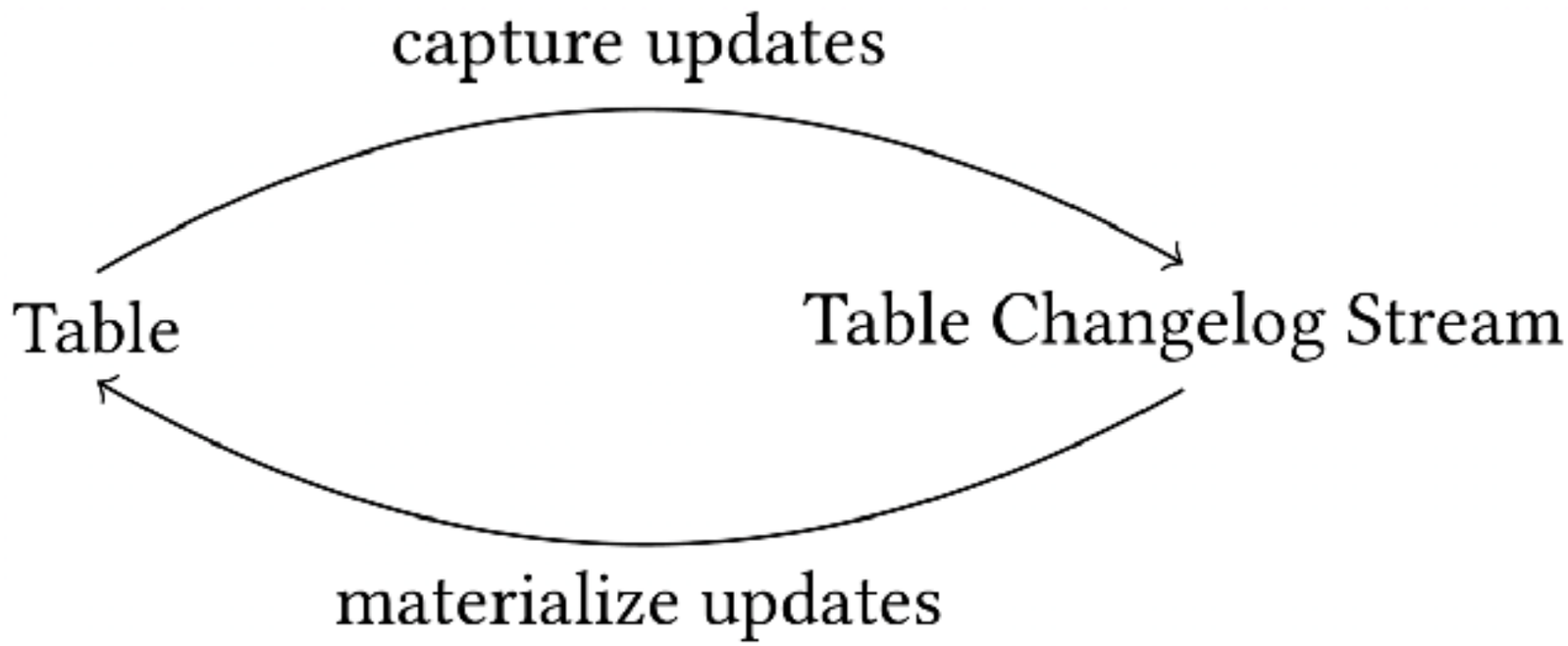
Dual Stream Model

The intuition



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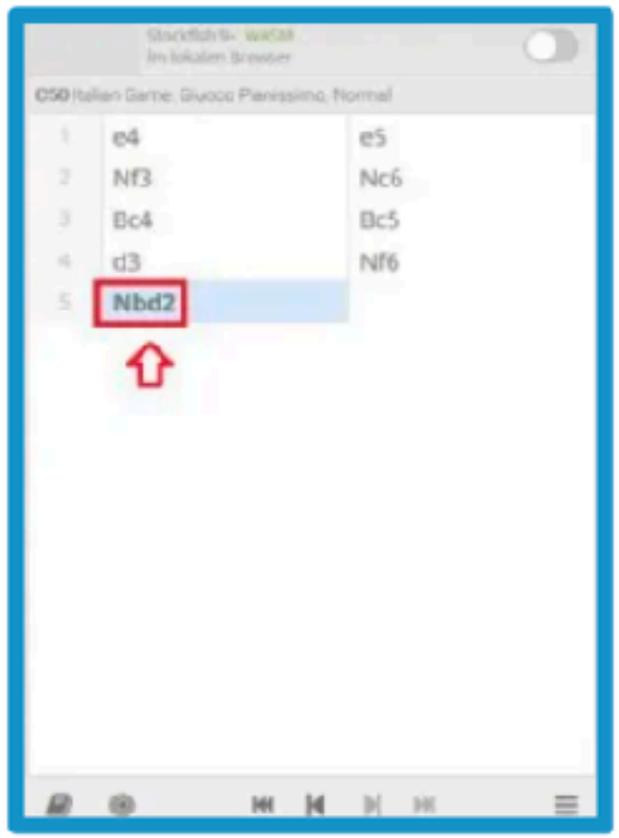
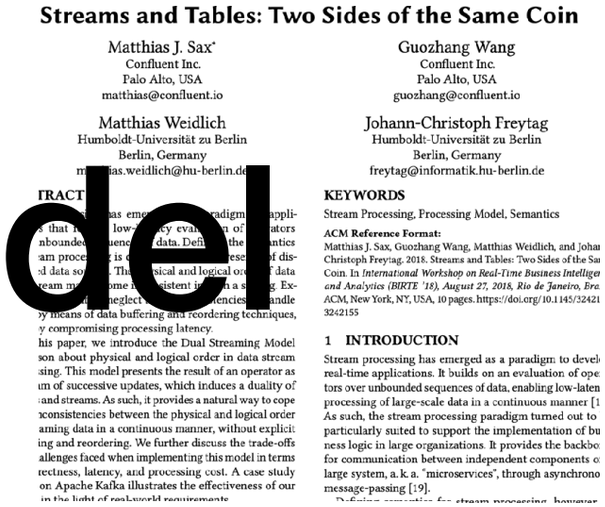


Streams record History
"The sequence of moves."

Tables represent State
"The state of the board at last move."

https://www.michael-noll.com/blog/2018/04/05/of-stream-and-tables-in-kafka-and-stream-processing-part1/



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TRACT

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Dual Stream Model

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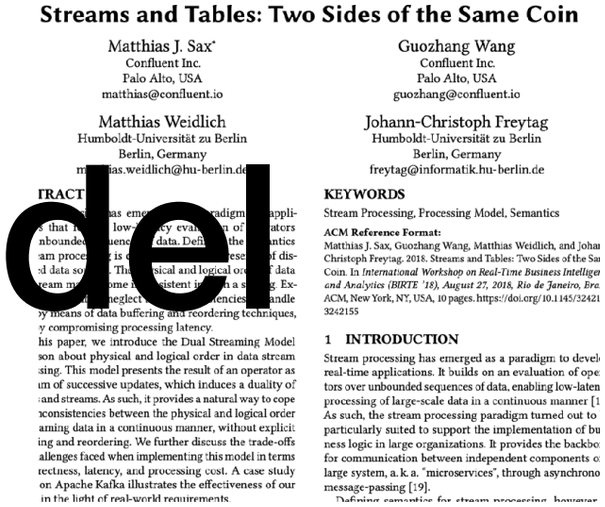

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Dual Stream Model

The Truth about Streams

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Unbounded and ordered sequence of key-value pairs

Stream

Change-log Stream

A streams whose records are updates to a table

records are identified by a primary key

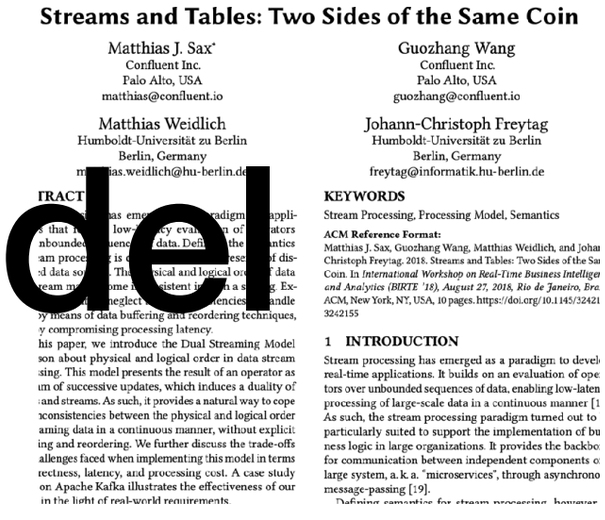
Record Stream

A streams whose records are facts

records are not identified by a primary key

Dual Stream Model

The Truth about Tables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1 INTRODUCTION

A table is a collection of table versions; one version for each point in time using the timestamp as a version number.

T(1)={T5 ={⟨A,7.2⟩}}

T(2) = {T5 = {⟨A,7.2⟩},T6 = {⟨B,14.7⟩}}

T(3) = {T5 = {⟨A,7.2⟩}, T6 = {⟨A,8.9⟩,⟨B,14.7⟩}}

T(4) = {T3 = {⟨B,12.1⟩},T5 = {⟨A,7.2⟩,⟨B,12.1⟩}, T6 = {⟨A, 8.9⟩, ⟨B, 14.7⟩}}

T(5) = {T3 = {⟨B,12.1⟩},T5 = {⟨A,7.2⟩,⟨B,12.1⟩}, T6 = {⟨A, 8.9⟩, ⟨B, 14.7⟩},T8 = {⟨A, 8.9⟩, ⟨B, 16.7⟩}}

Dual Stream Mod

The Truth about Operations

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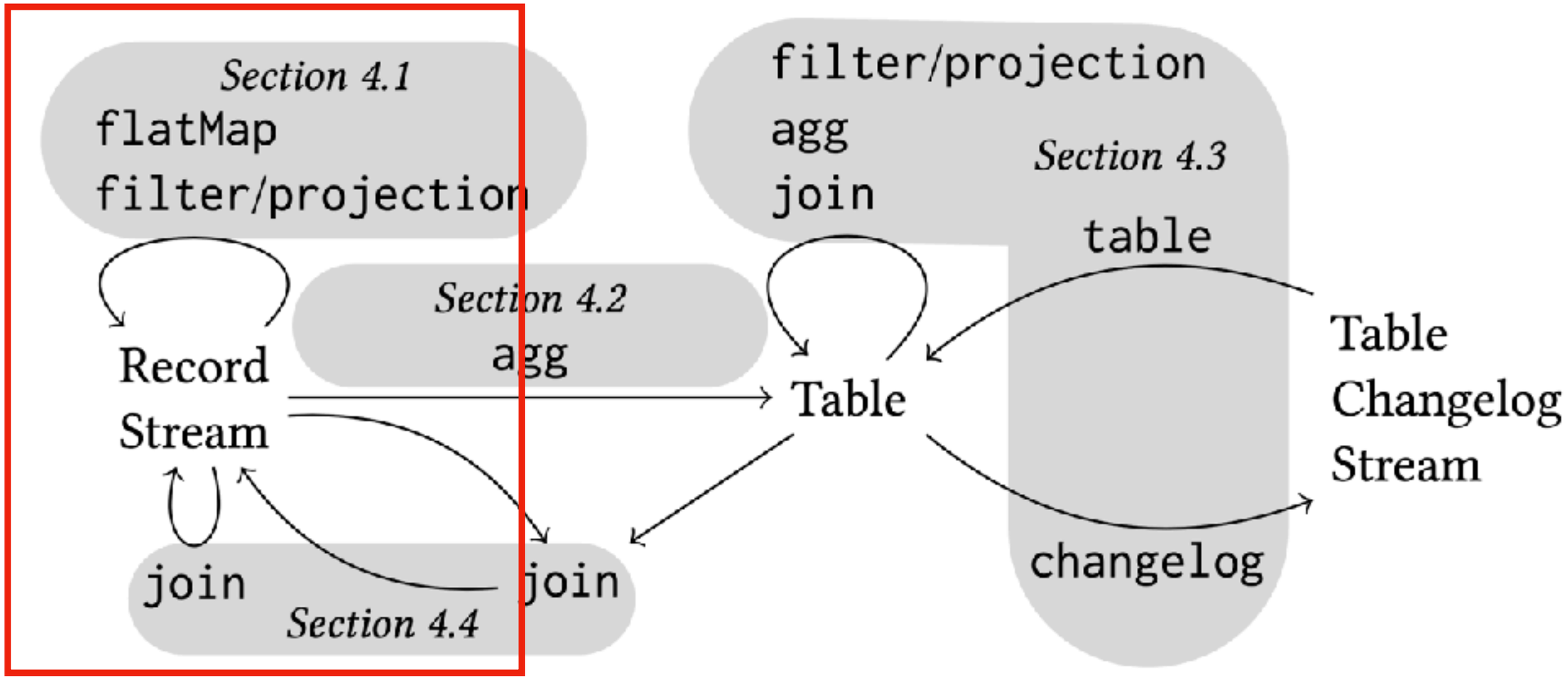
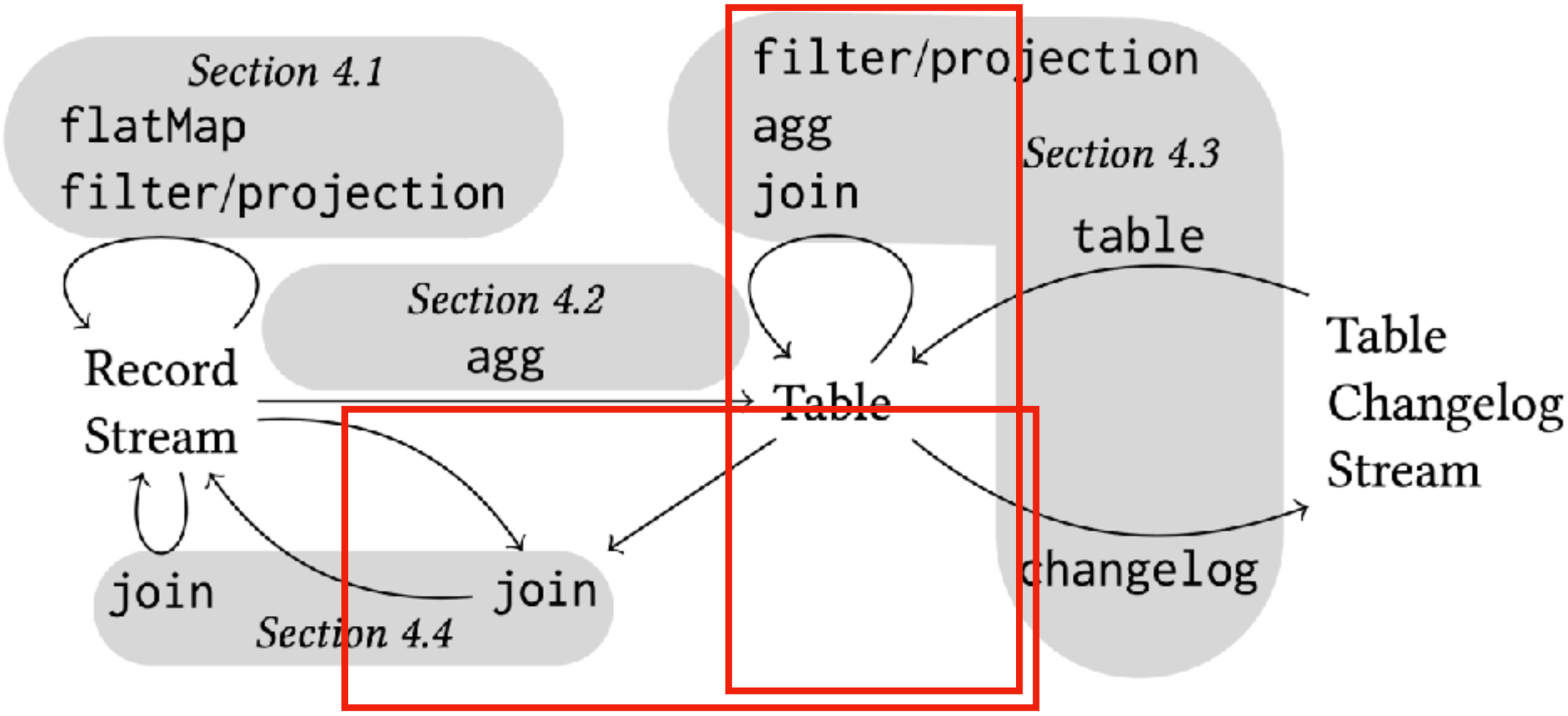


Stateless Operations

Dual Stream Mod

The Truth about Operations



Stateful Operations

Streams and Tables: Two Sides of the Same Coin

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TRACT

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s that require low-latency evaluation of operators
nbounded sequences of data. Defining the semantics
am processing is challenging in the presence of dis-
d data sources. The physical and logical order of data
eam may become inconsistent in such a setting. Ex-
models either neglect these inconsistencies or handle
y means of data buffering and reordering techniques,
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KEYWORDS

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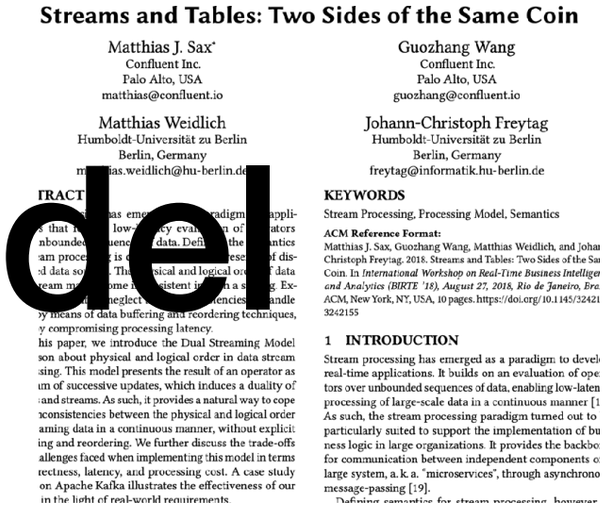
Dual Stream Model

The Complete Picture



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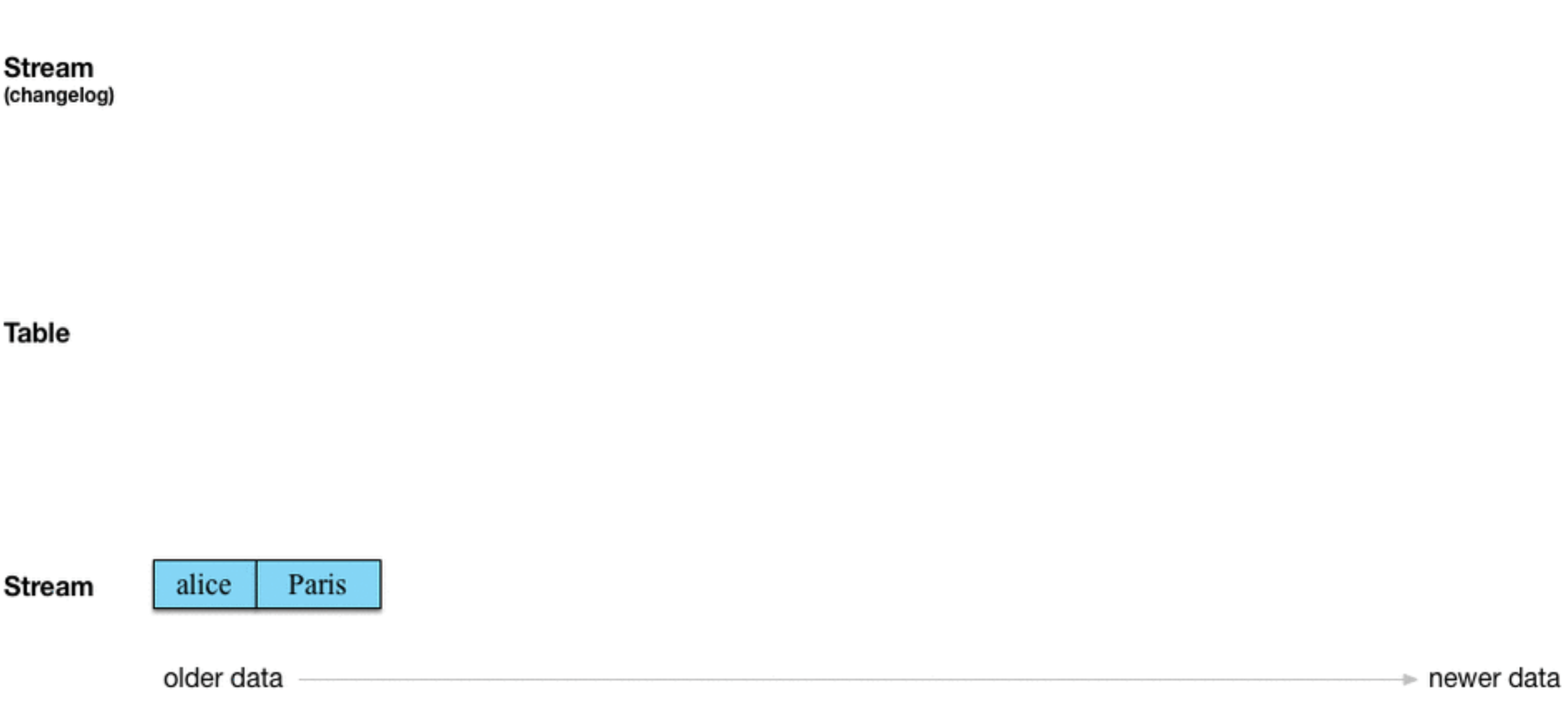
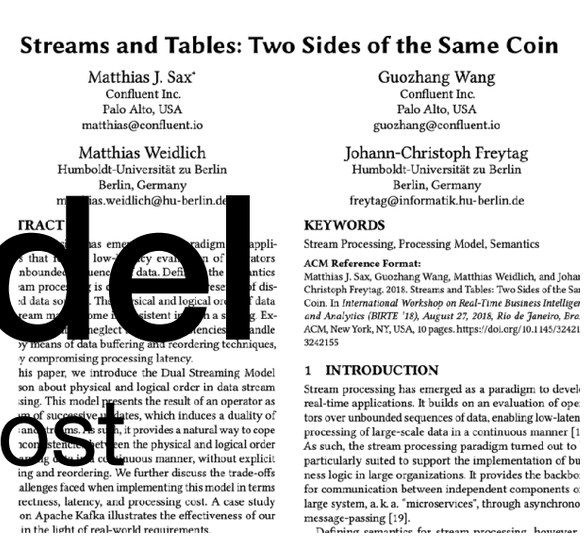
Defining semantics for stream processing, however



https://www.michael-noll.com/blog/2018/04/05/of-stream-and-tables-in-kafka-and-stream-processing-part1/

Dual Stream Model

Result Correctness vs Runtime Cost



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1 INTRODUCTION

The DSM simplifies the **reasoning** about the **transformations**, but does not solve the **unboundedness** problem.

We still need infinite memory for processing an infinite stream.

DSM introduces the retention time to make the trade-off explicit.

Mapping to Kafka

Minimal

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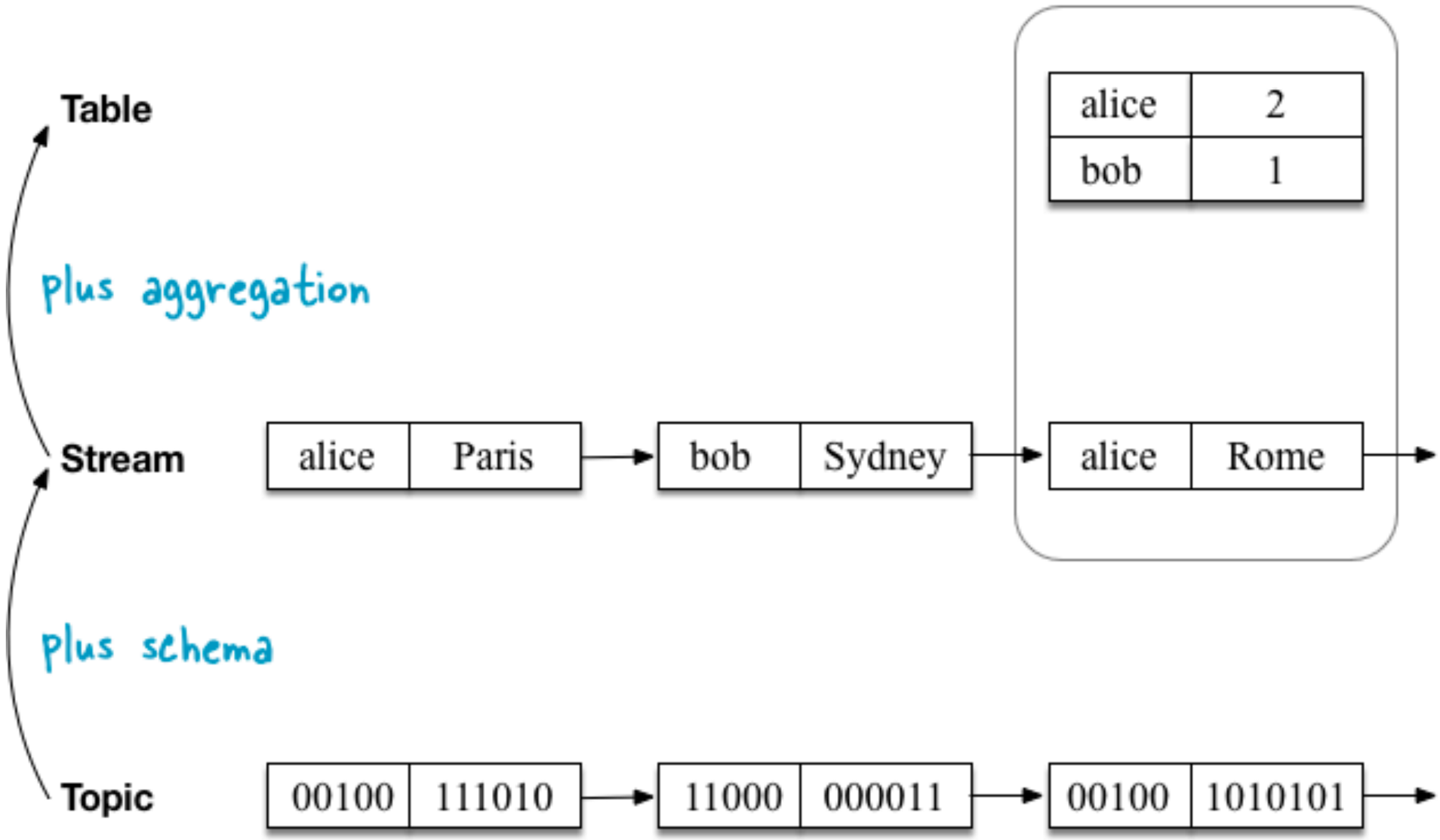

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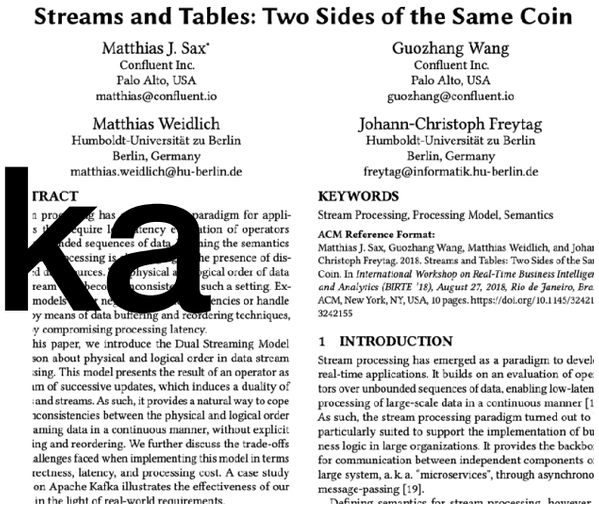

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1 INTRODUCTION

Concept	Partitioned	Unbounded	Ordering	Mutable	Unique key	Schema
Topic	Yes	Yes	Yes	No	No	No (raw
Stream	Yes	Yes	Yes	No	No	Yes
Table	Yes	Yes	No	Yes	Yes	Yes

Concept	Kafka	KSQL	Java	Scala	Python
Topic	-	-	`List/Stream`	`List/Stream[(Array[Byte],`	`[]`
Stream	`KStream`	`STREAM`	`List/Stream`	`List/Stream[(K, V)]`	`[]`
Table	`KTable`	`TABLE`	`HashMap`	`mutable.Map[K, V]`	`{}`

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Streaming SQL

- New trend is hiding the complexity of the processing behind SQL
- Like CQL, but even simpler.
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One SQL to Rule Them All:
An Efficient and Syntactically Idiomatic Approach to Management of Streams and Tables

An Industrial Paper

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ABSTRACT

Real-time data analysis and management are increasingly critical for today's businesses. SQL is the de facto lingua franca for these endeavors, yet support for robust streaming analysis and management with SQL remains limited. Many approaches restrict semantics to a reduced subset of features and/or require a suite of non-standard constructs. Additionally, use of event timestamps to provide native support for analyzing events according to when they actually occurred is not pervasive, and often comes with important limitations.

We present a three-part proposal for integrating robust streaming into the SQL standard, namely: (1) time-varying relations as a foundation for classical tables as well as streaming data, (2) event time semantics, (3) a limited set of optional keyword extensions to control the materialization of time-varying query results. Motivated and illustrated using examples and lessons learned from implementations in Apache Calcite, Apache Flink, and Apache Beam, we show how with these minimal additions it is possible to utilize the complete suite of standard SQL semantics to perform robust stream processing.

CCS CONCEPTS

• **Information systems** → **Stream management**; **Query languages**;

KEYWORDS

stream processing, data management, query processing

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1 INTRODUCTION

The thesis of this paper, supported by experience developin large open-source frameworks supporting real-world stream ing use cases, is that the SQL language and relational mod ns is and with minor non-intrusive extensions, can be ver effective for manipulation of streaming data.

Our motivation is two-fold. First, we want to share our

Thanks!

Questions?