Streaming Data Engineering
A Tale of Three Streams

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1st premises: continuity matters

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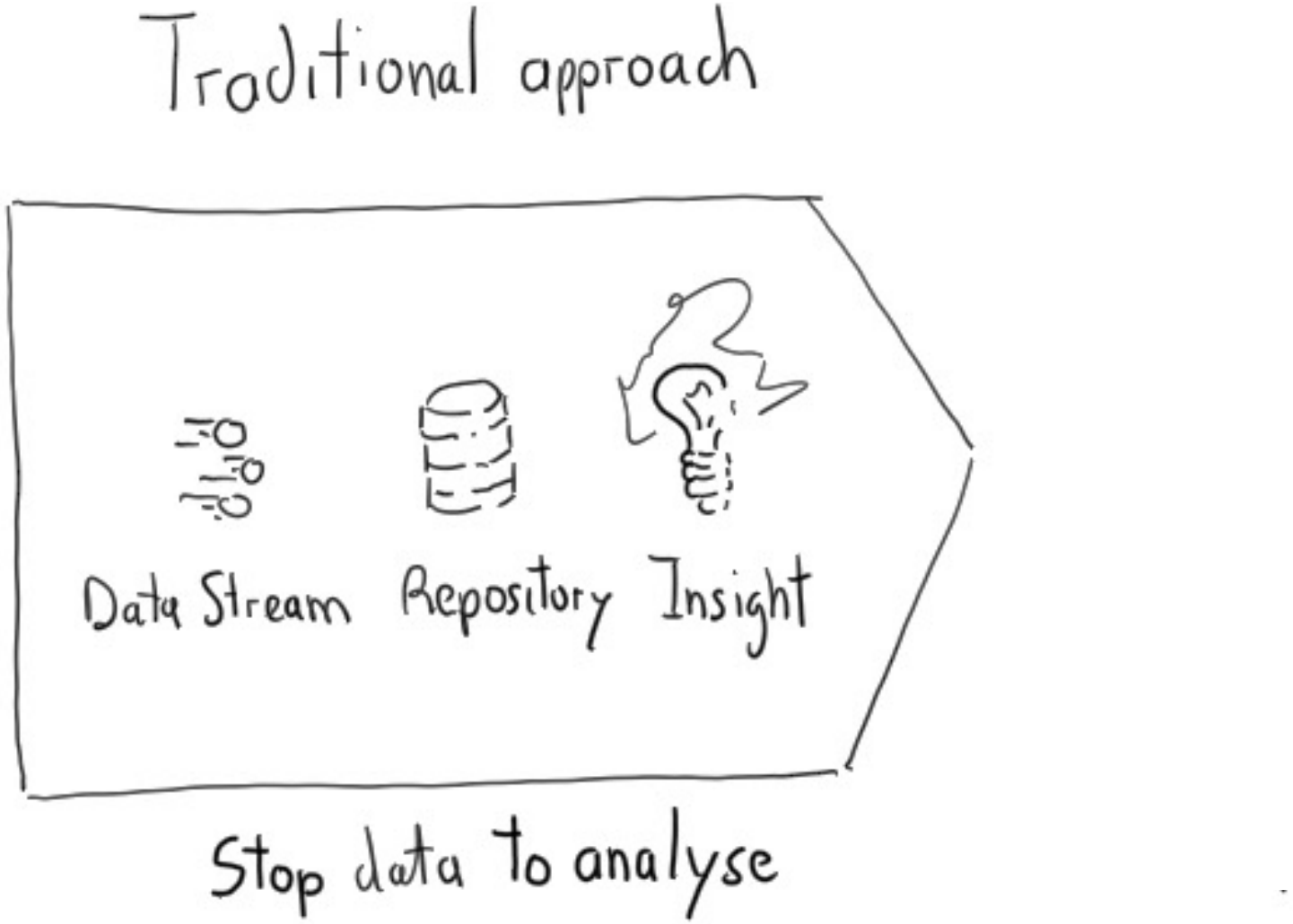
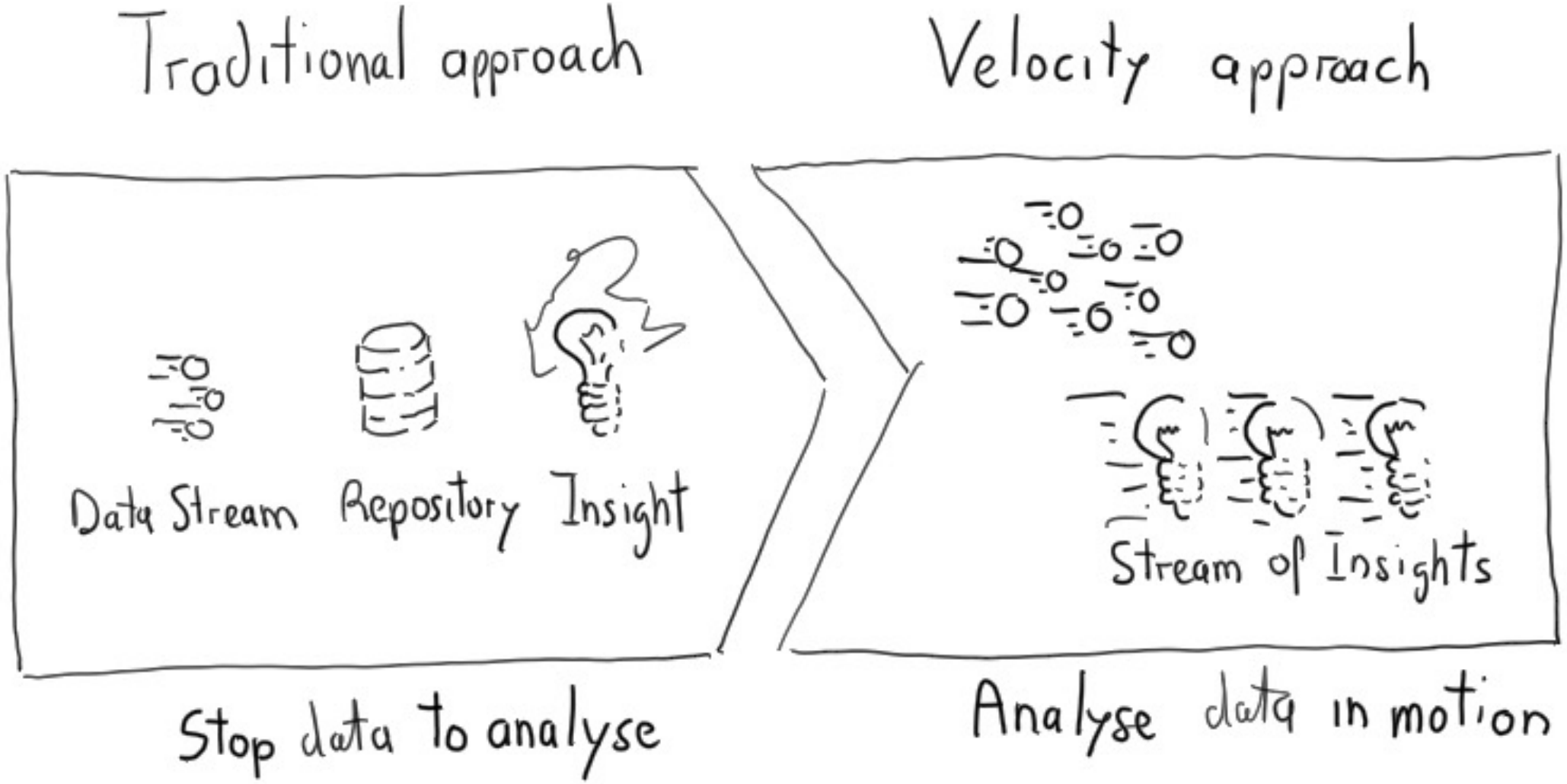
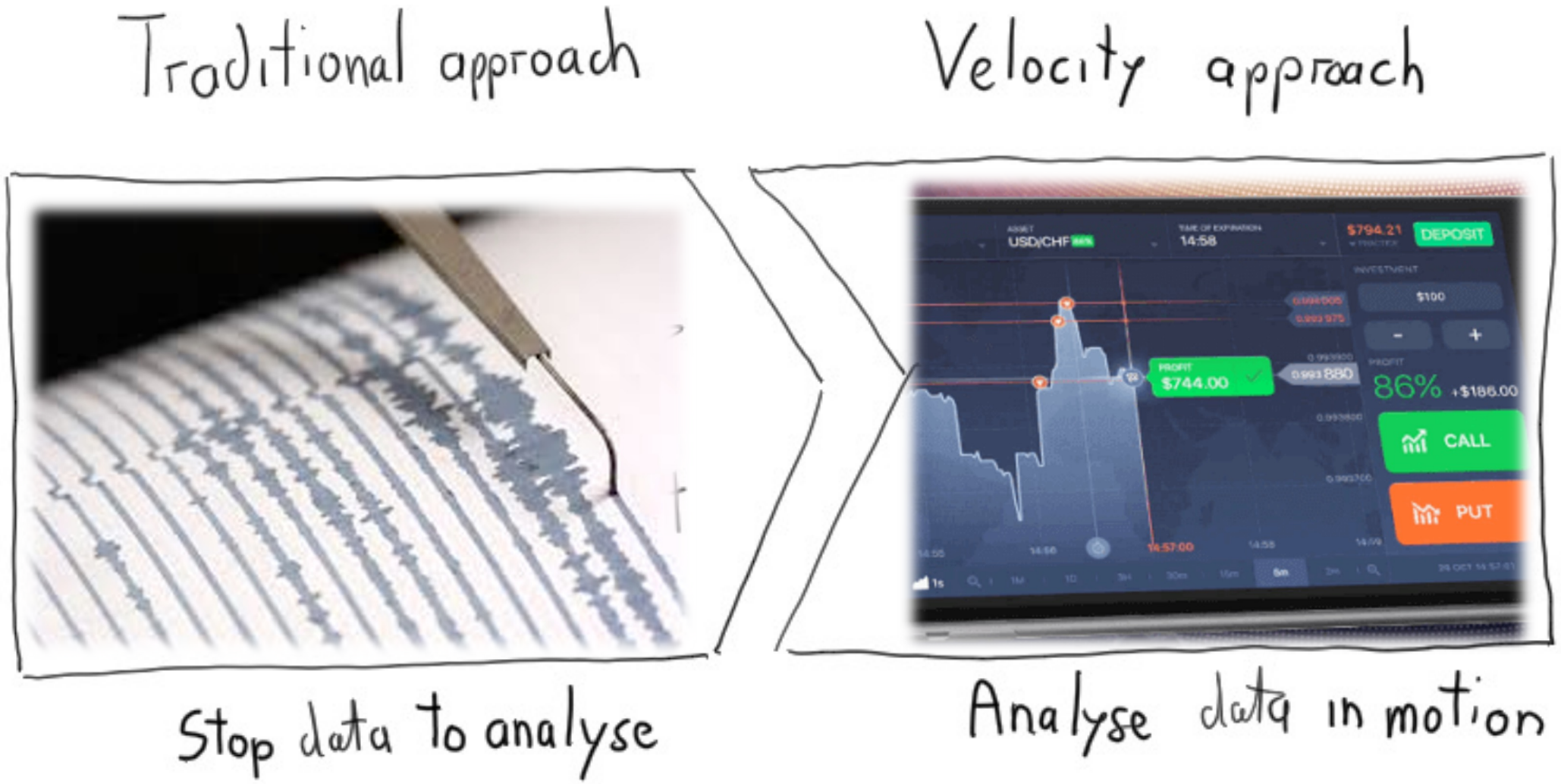


1st premises: continuity matters



1st premises: continuity matters



Stream: a useful metaphor to explore the solution space

Streams take many forms …

Myriads of **tiny** flows that you can **collect**

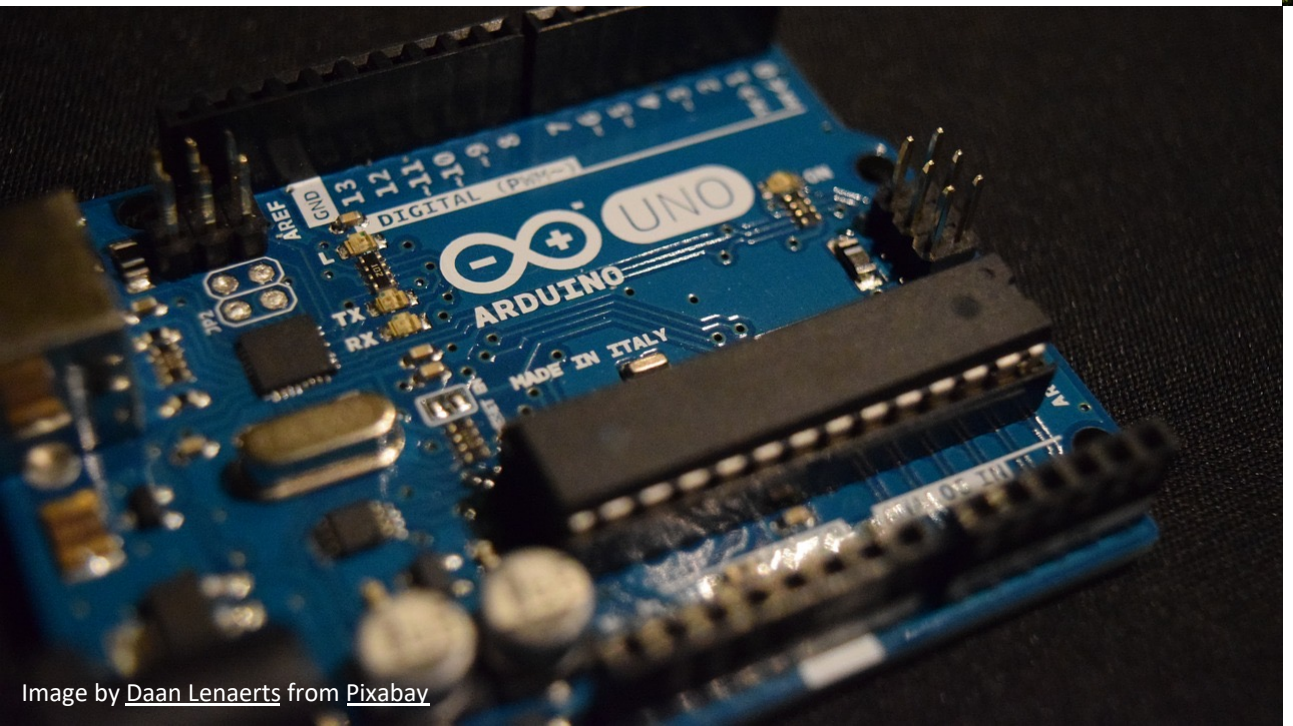


Image by Daan Lenaerts from Pixabay

e.g., **from** physical or software **sensors**

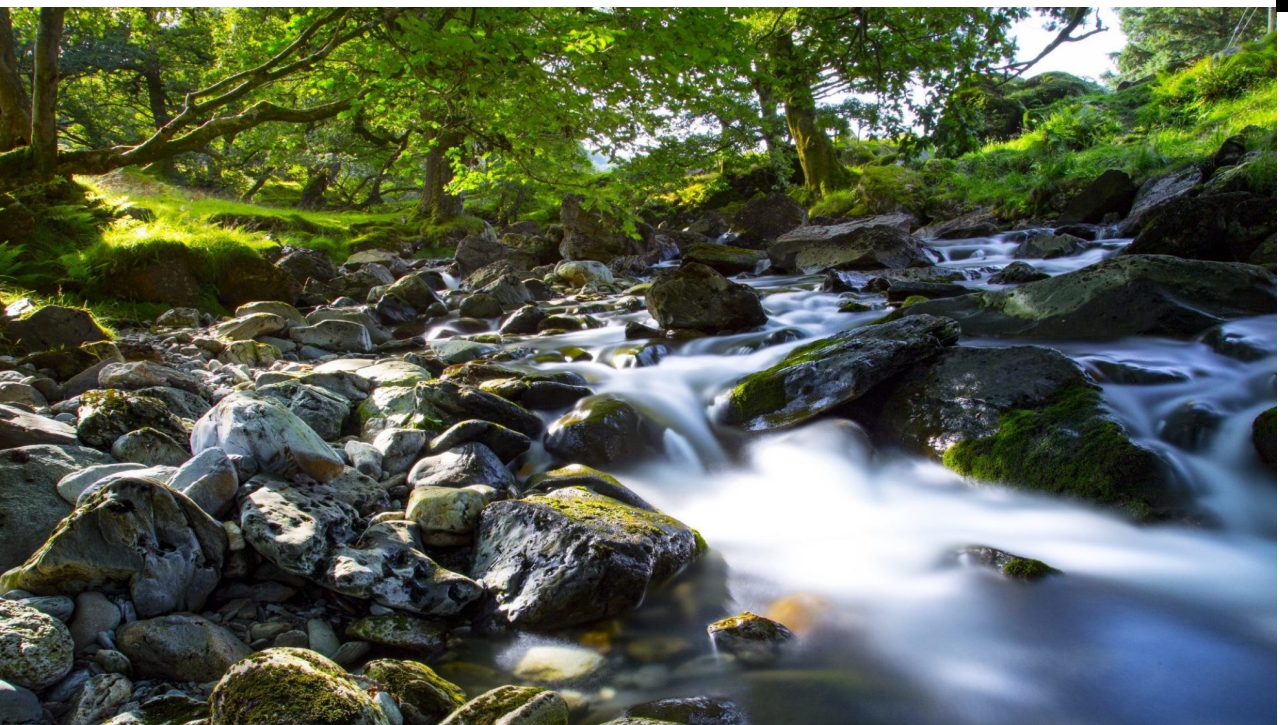
Continuous massive flows than you **cannot stop**

Image by Bruno /Germany from Pixabay

e.g., **social media,** telcos' and utilities' **monitoring**

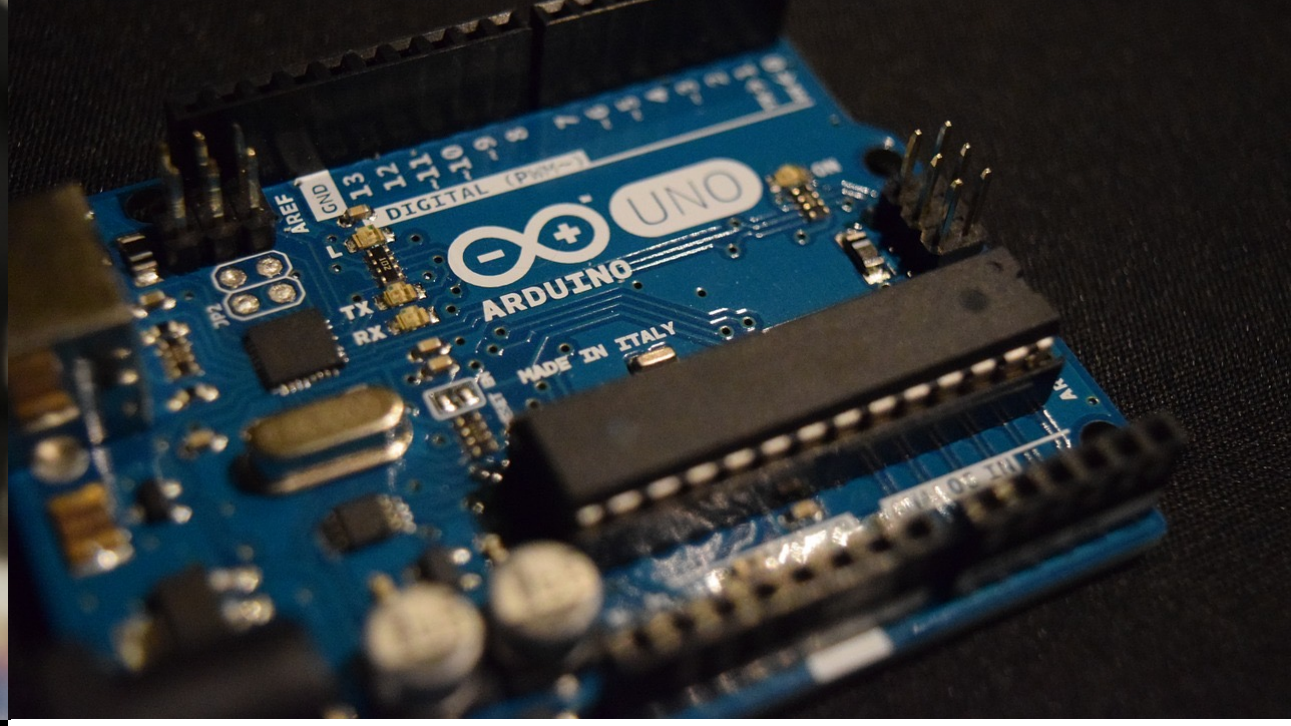
e.g., physical or cyber **alarms**

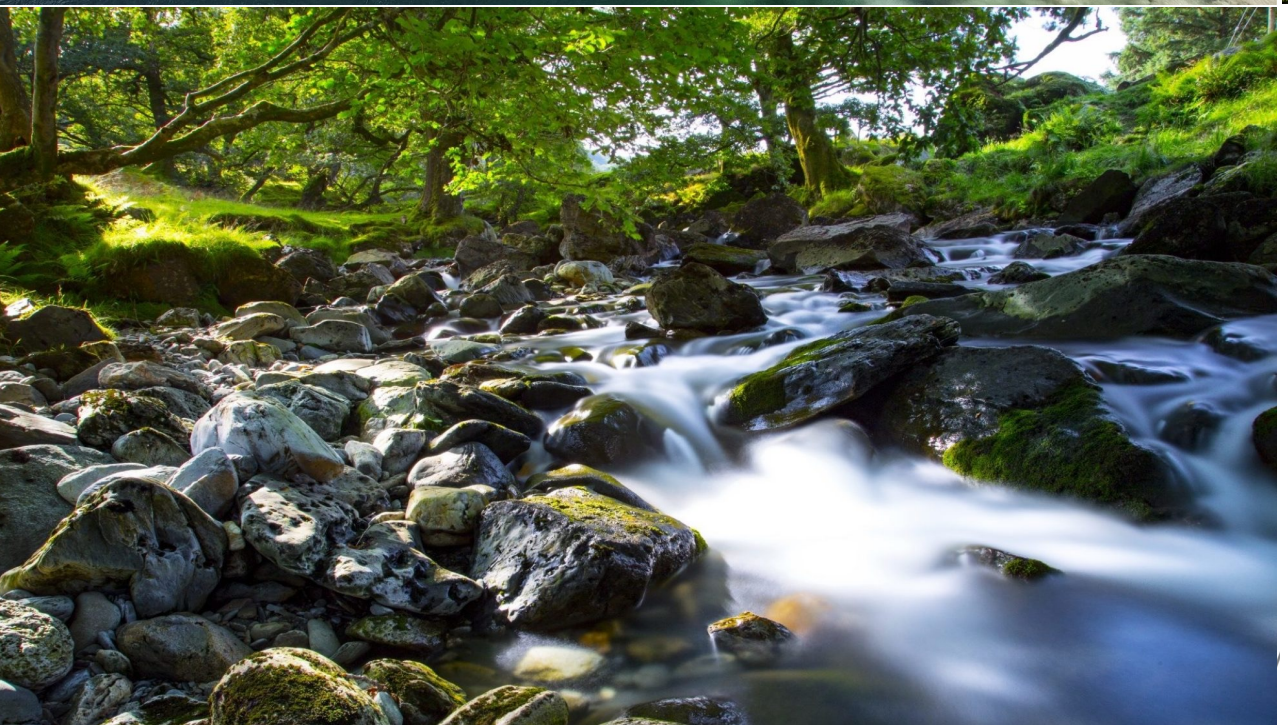

Image by Dieter zabel from Pixabay



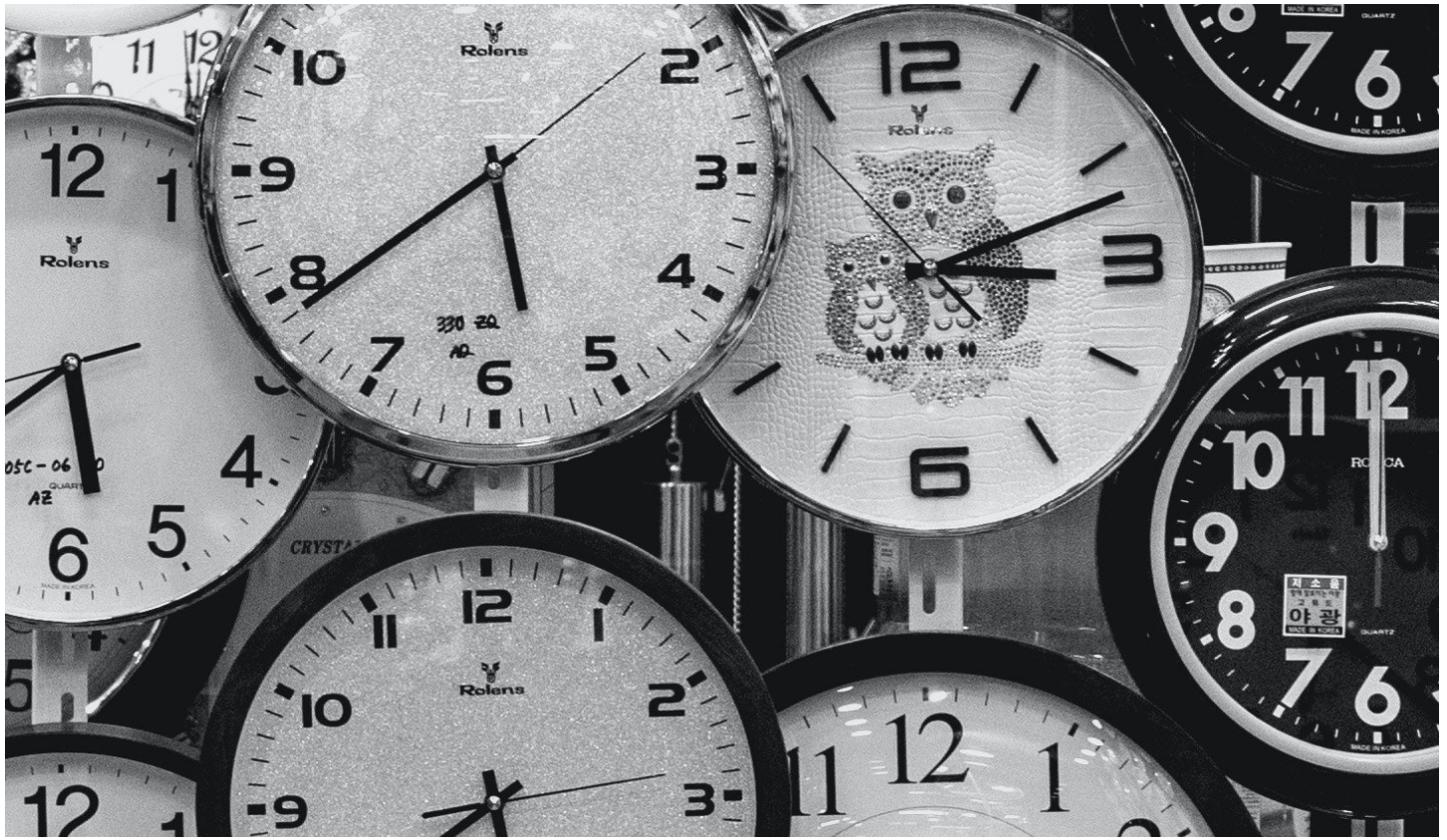
Continuous numerous flows that **can** turn into a **torrent**


SAT 1
HIGH
LOW
SAT 2
MSE 1724 K
Cascade Multi Switch


ARDUINO
UNO
DIGITAL
MADE IN ITALY

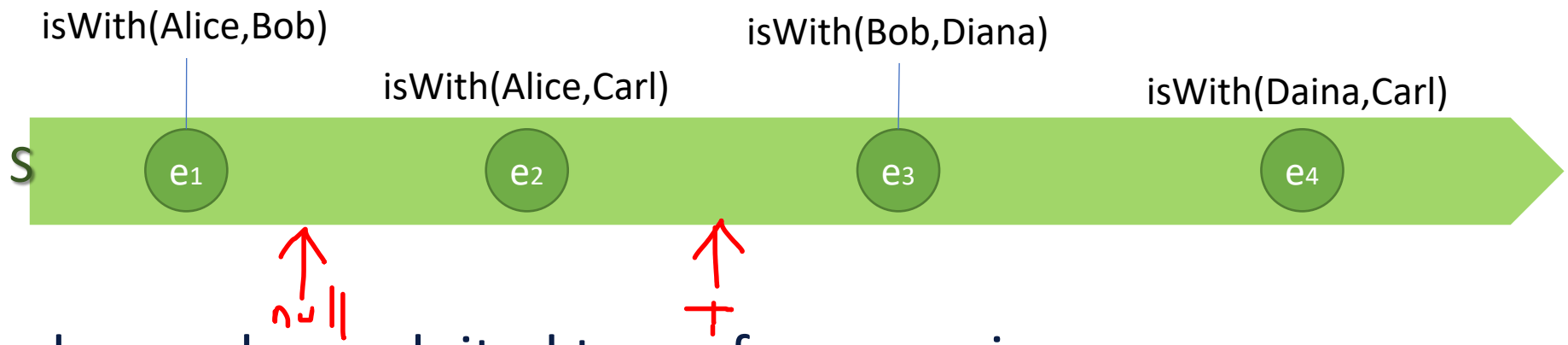


2nd premises: time (models) matters!



Stream-only Time Model

too little



- The order can be exploited to perform queries
  - Does Alice meet Bob **before** Carl?
  - Who does Carl meet **first**?

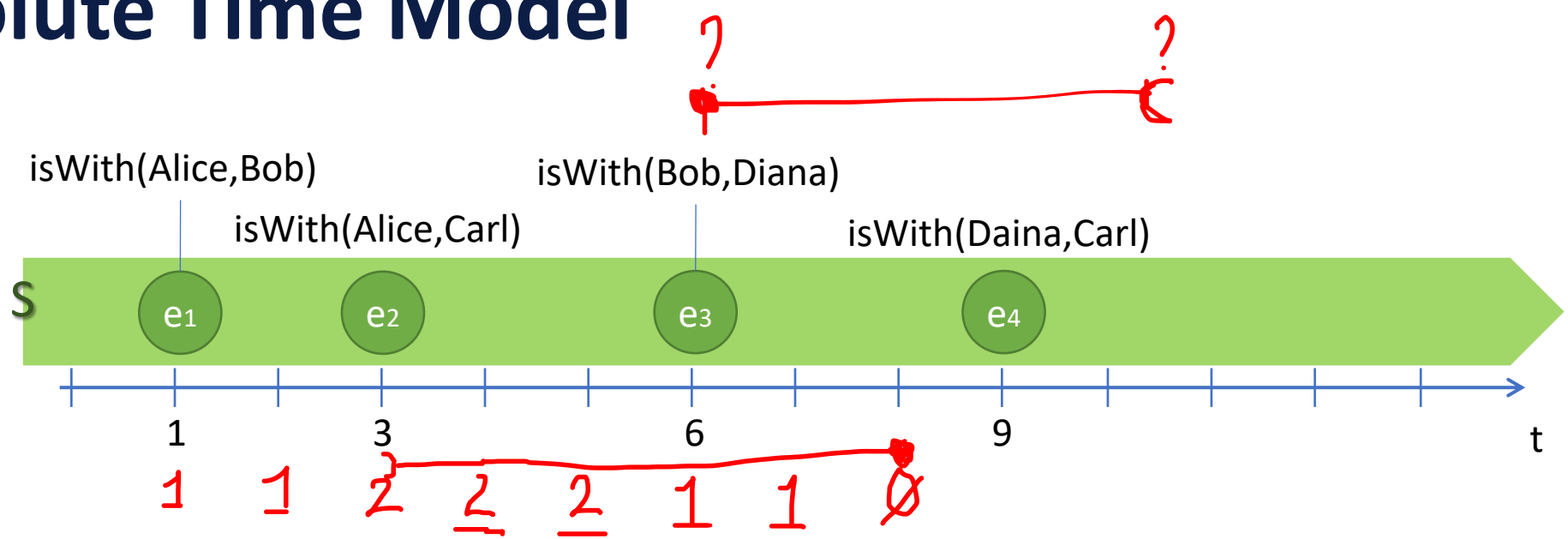
forget when ans.

cnt (Alice)

last

no forget

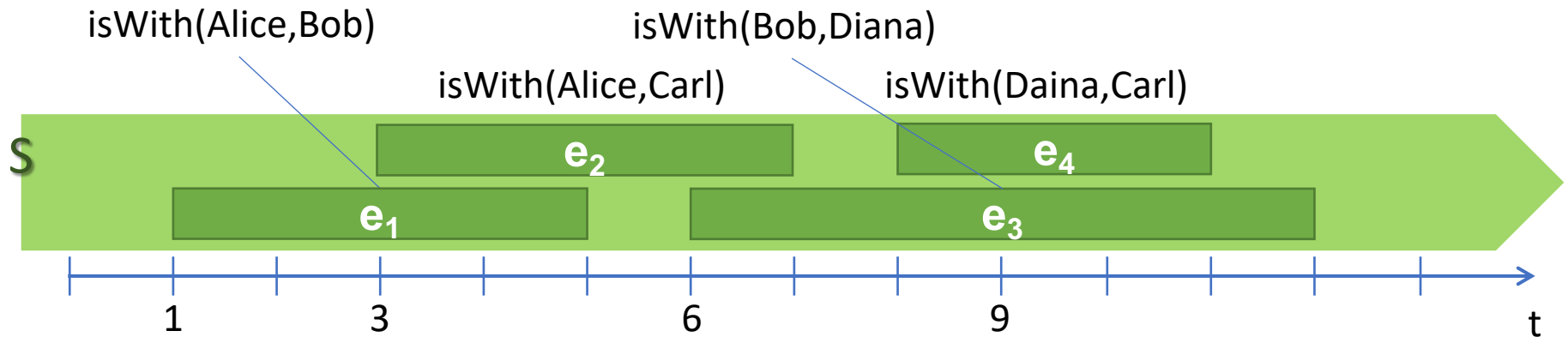
Absolute Time Model



- We can ask the queries in the previous slide
- We can start to compose queries taking into account the time
  - How many people has Alice met **in the last 5m**?
  - Does Diana meet Bob and then Carl **within 5m**?

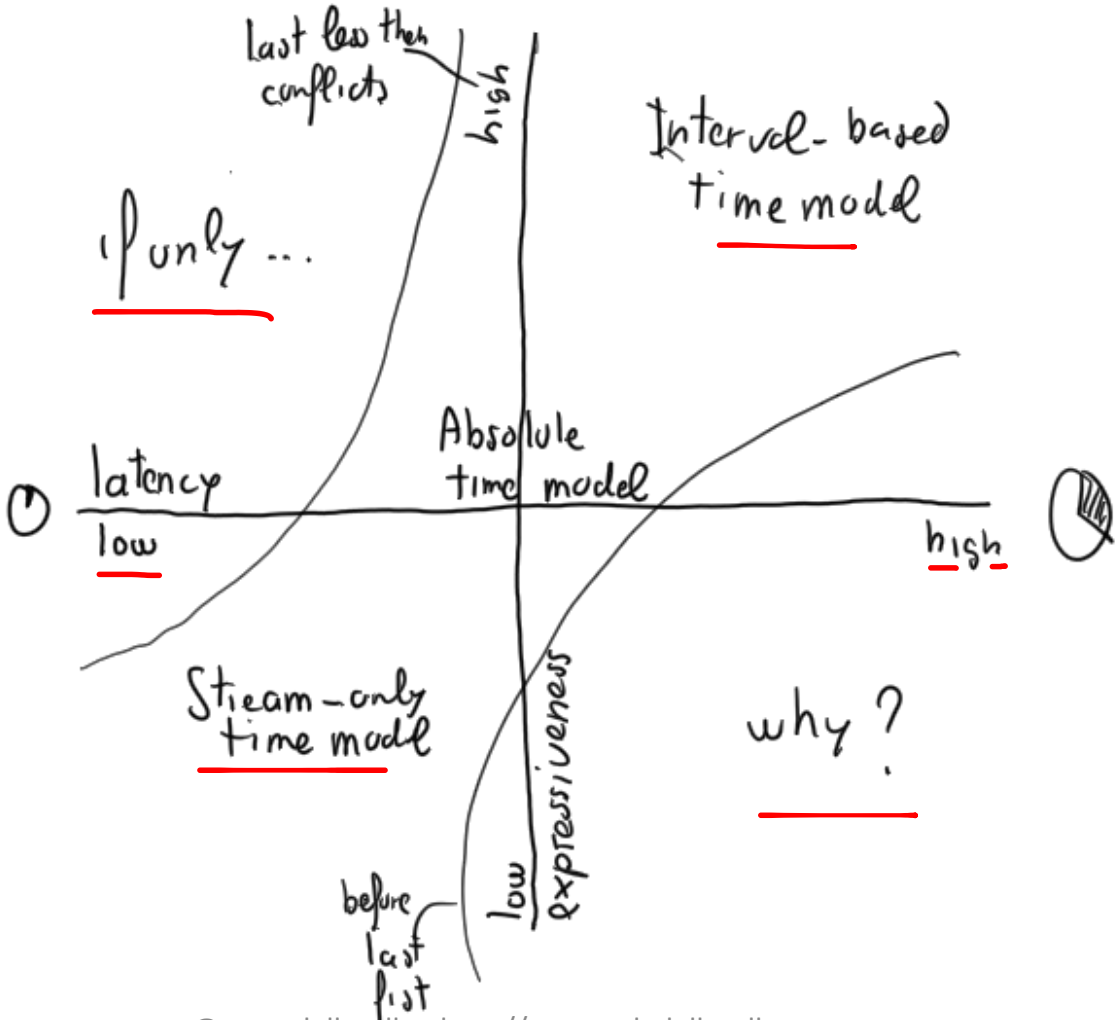
Interval-base Time Model

too much



- We can ask the queries in the previous two slides
- It is possible to write even more complex queries:
  - Which are the meetings the **last less than 5m**?
  - Which are the meetings with **conflicts**?

A first trade-off: latency vs. expressiveness



Can we tame data velocity?

Image by Pexels from Pixabay

On Events and decoupling

Events

an immutable and append-only stream of “business facts”

Decoupling

means decentralizing the freedom to act, adapt, and change

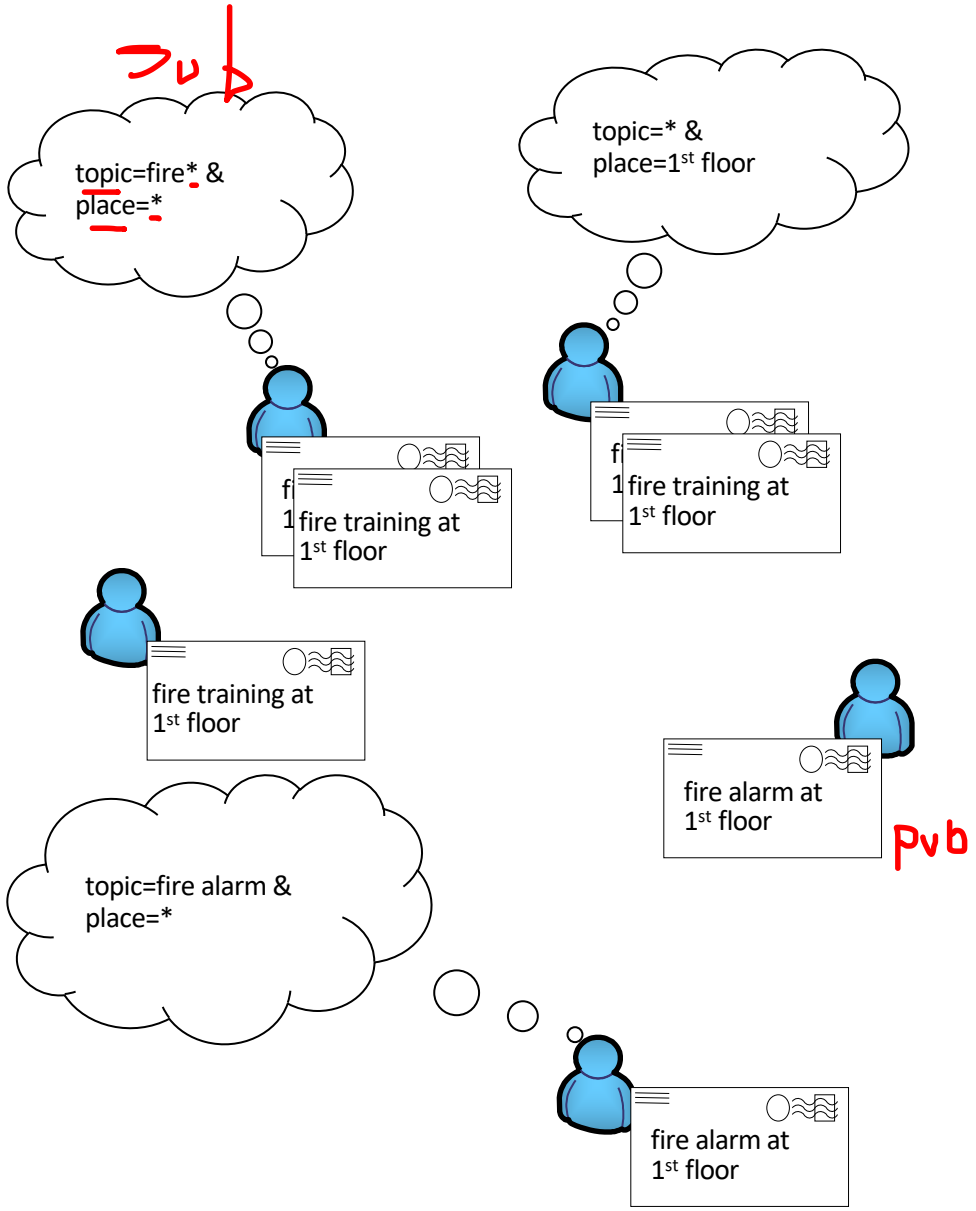
Event-based systems

- Events as “first-class” entities
- Services emit and consume events asynchronously
- Better decoupling with respect to APIs (no temporal coupling)

Eugster, P. T., Felber, P. A., Guerraoui, R., & Kermarrec, A. M. (2003). **The many faces of publish/subscribe.** *ACM computing surveys (CSUR)*, *35*(2), 114-131.

Publish/subscribe

- Components
  - collaborate by exchanging *events*
  - *publish events they observe*
  - *subscribe* to the events they are interested in
- Communication is:
  - Purely message based
  - Asynchronous
  - Multicast
  - Implicit
  - Anonymous



Event-driven architecture @ Netflix

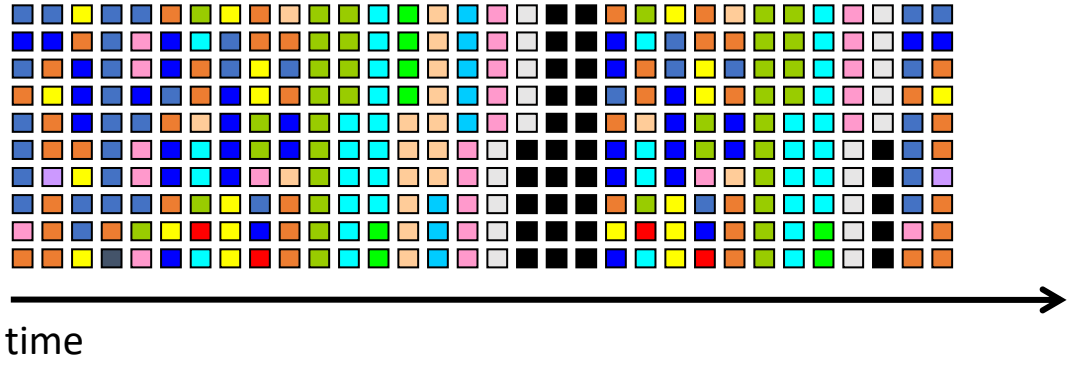
[src. https://labs.sogeti.com/microservices-architectures-stay/]

10:45


Taming
Continuous massive flows
than you cannot stop
with
Data Stream Mng. Systems

Data Stream Management Systems (DSMS)

- Data streams are (**unbounded**) sequences of time-varying data elements
- Represent:
  - an (almost) “continuous” flow of information
  - with the recent information being more relevant as it describes the current state of a dynamic system



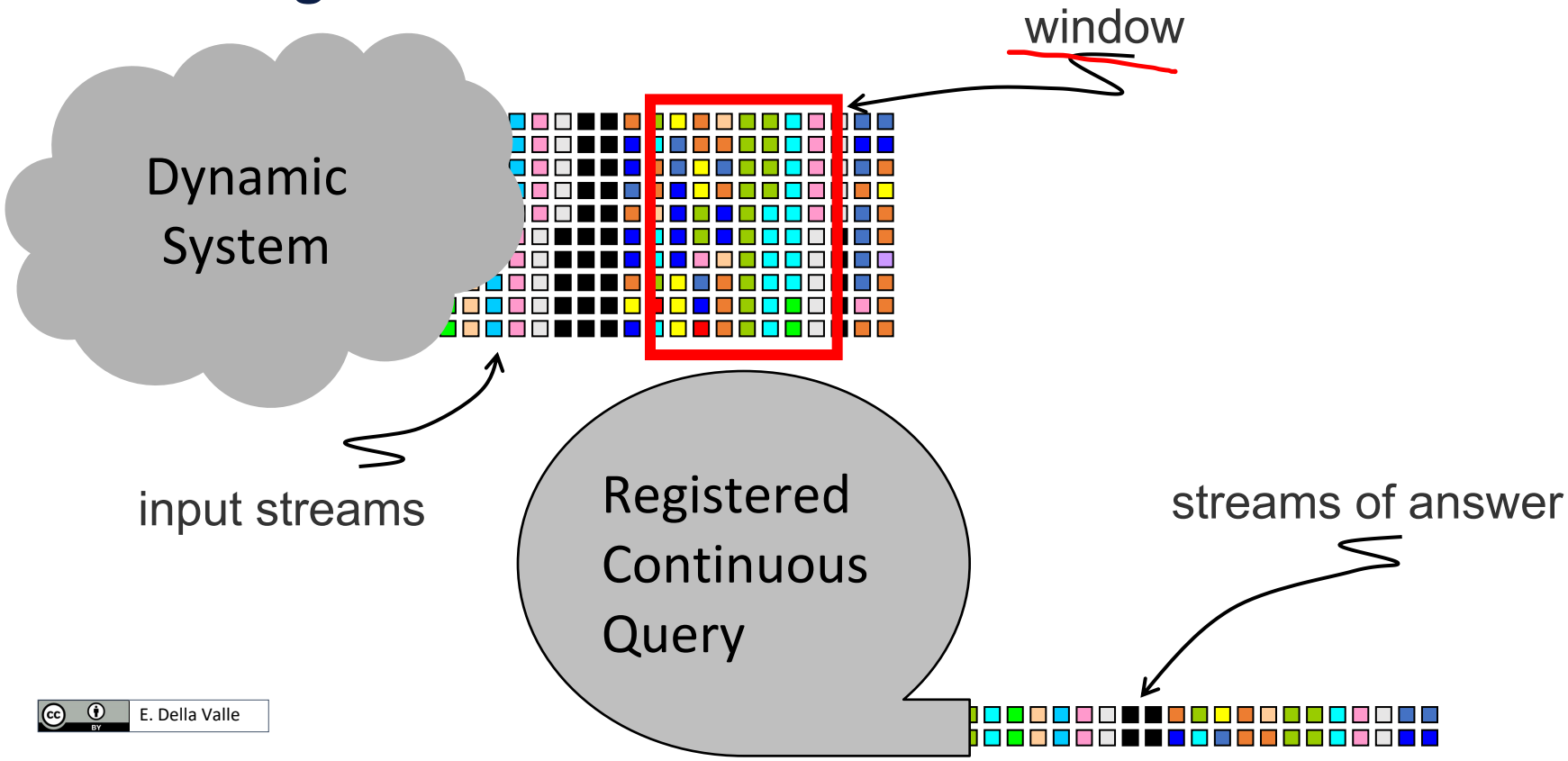
Data Stream Management Systems (DSMS)

- The nature of streams requires a paradigmatic change*
  - **from persistent data**
    - one time semantics
  - **to transient data**
    - continuous semantics

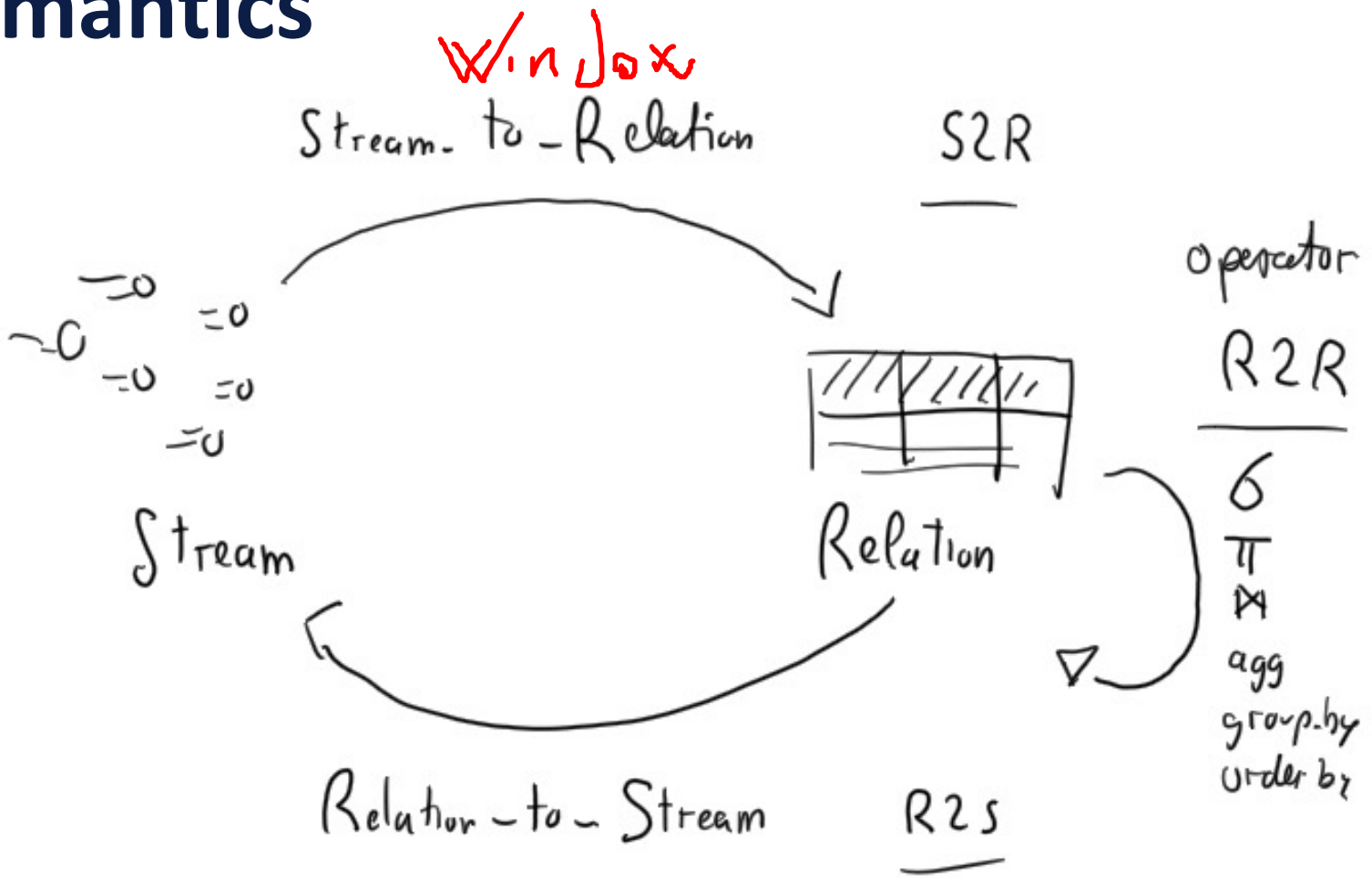
* This paradigmatic change first arose in DB community in **the late '90s**

Continuous Semantics

- Continuous **queries registered** over streams that are observed trough **windows**

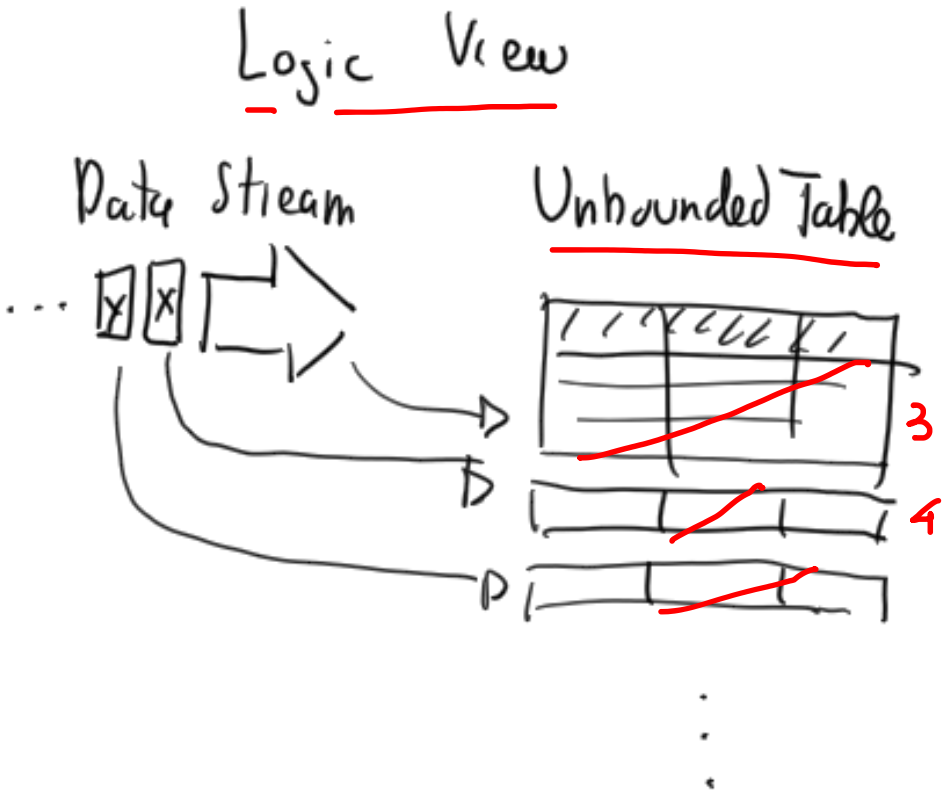


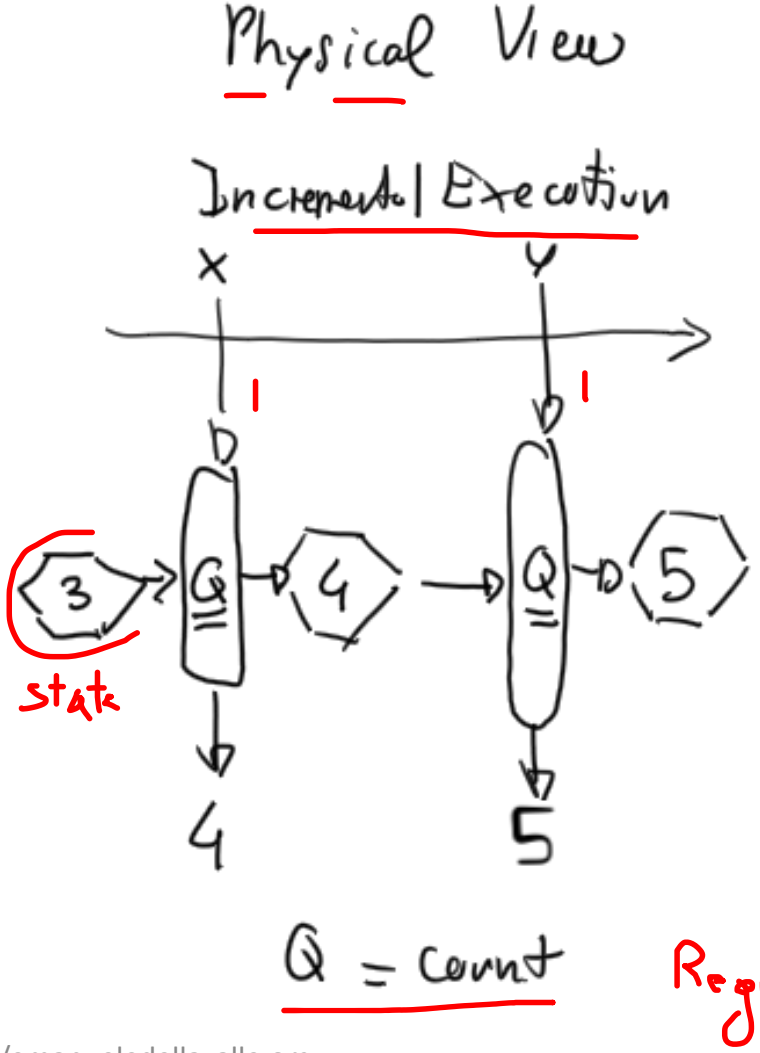
DSMS Semantics



Arasu, A., Babu, S. and Widom, J., 2006. **The CQL continuous query language: semantic foundations and query execution**. *The VLDB Journal*, *15*(2), pp.121-142.

Modern DSMS


Logic View
Data Stream
Unbounded Table
3
4


Physical View
Incremental Execution
X
Y
1
1
3
Q
4
Q
5
state
4
5
Q = count
Registred

SQL Extensions

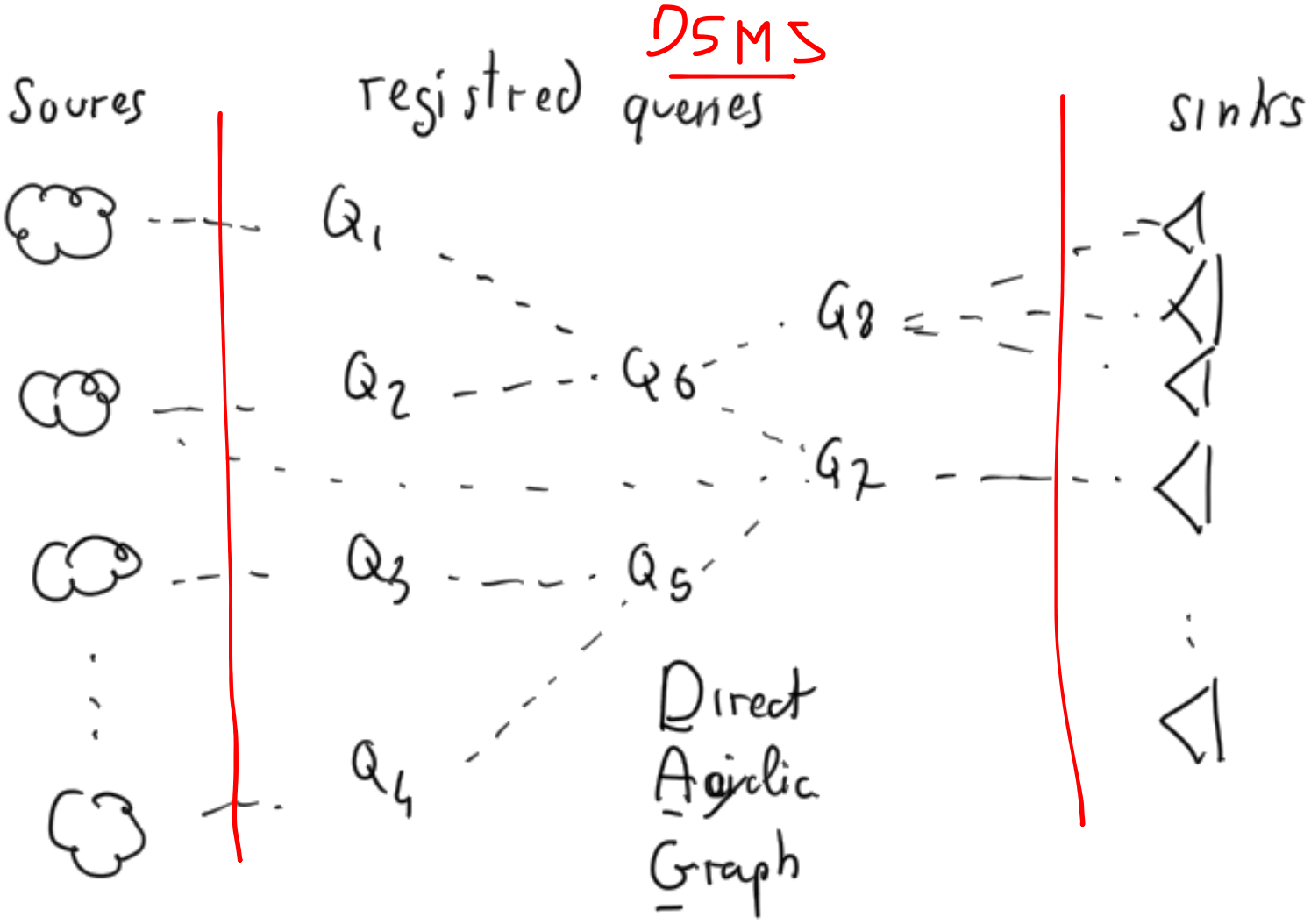
Windowed aggregation

```
SELECT x, COUNT(*), SUM(y)
FROM s1 WINDOW
    TUMBLING (SIZE 1 MINUTE)
GROUP BY x
EMIT CHANGES;
```

Join two streams together

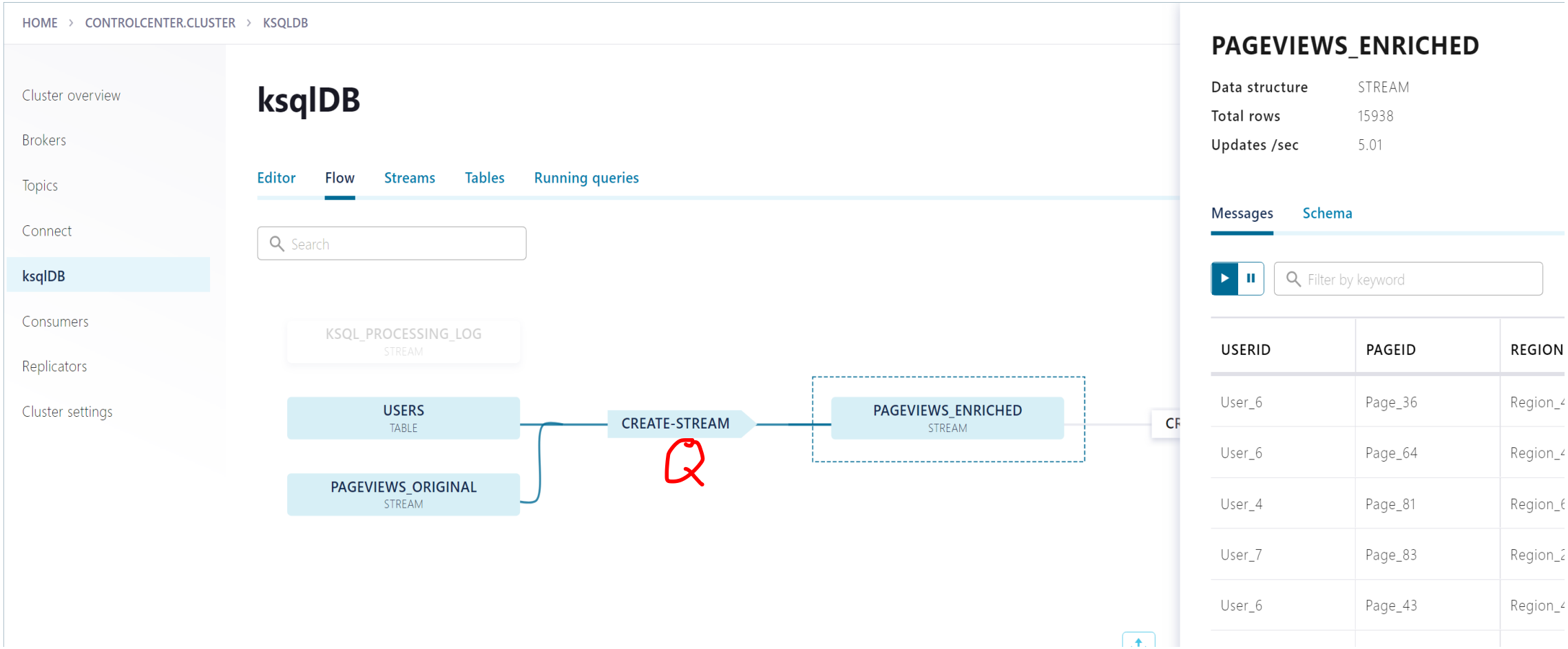
```
CREATE STREAM s3 AS
SELECT s1.c1, s2.c2
FROM s1 JOIN s2
  WITHIN 5 MINUTES
  ON s1.c1 = s2.c1
EMIT CHANGES;
```

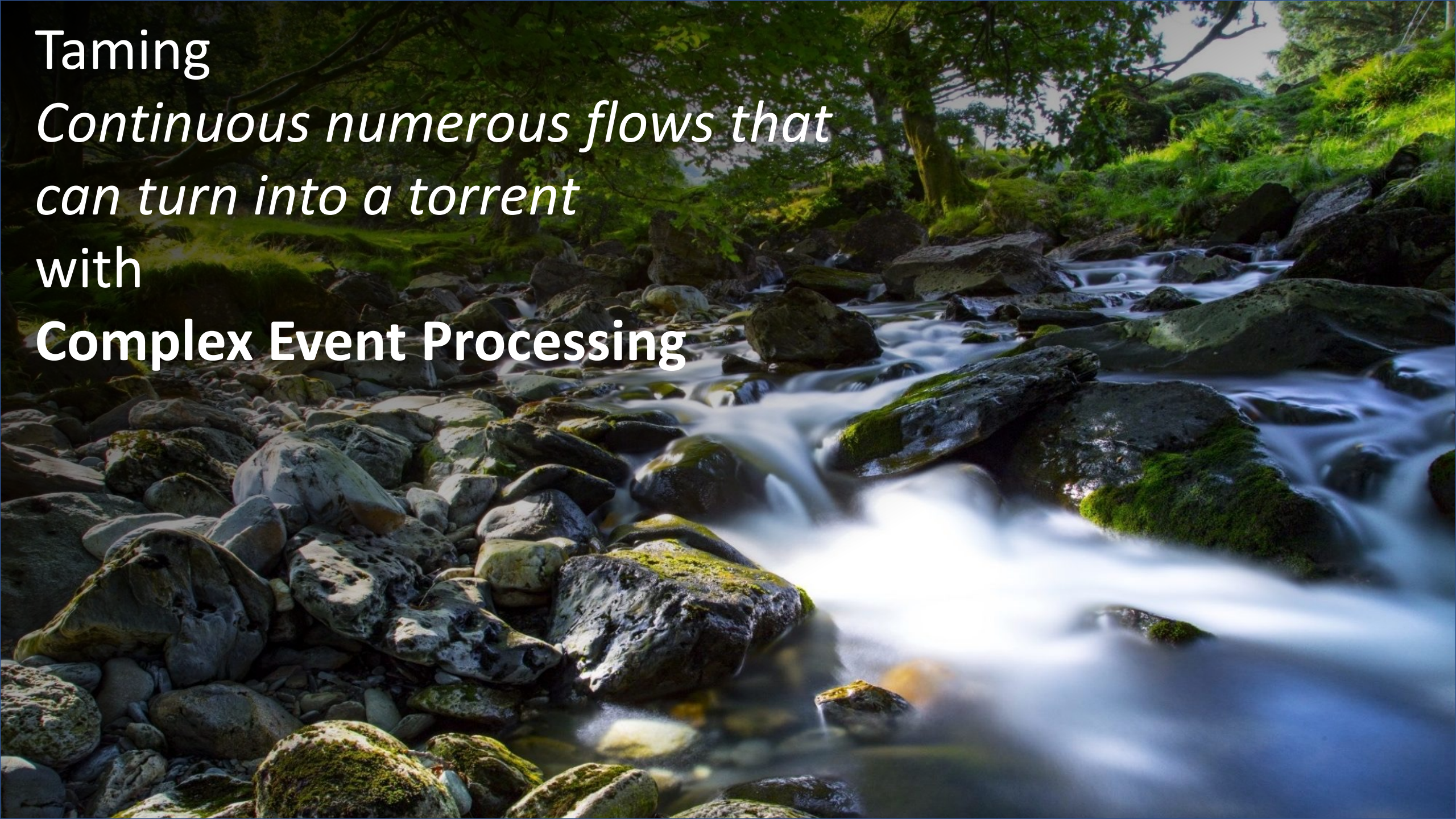
Typically queries are placed in a network



Typically queries are placed in a network

[src: https://docs.confluent.io/platform/current/control-center/ksql.html]




Taming
Continuous numerous flows that
can turn into a torrent
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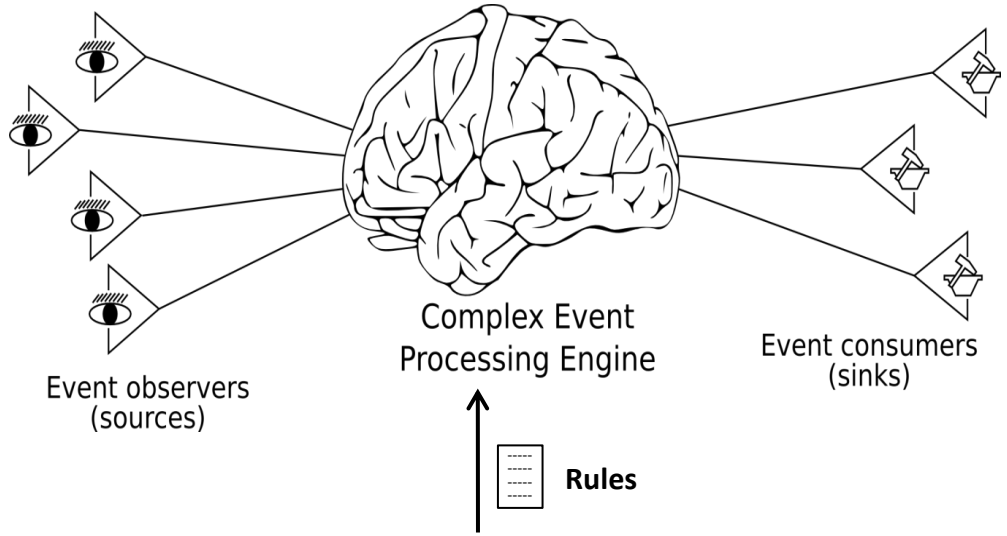
Complex Event Processing

Complex Event Processing (CEP)

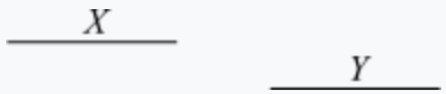
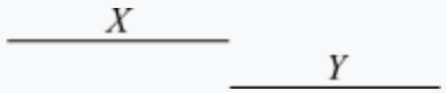
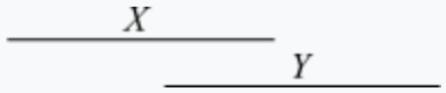
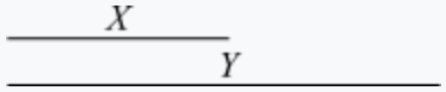
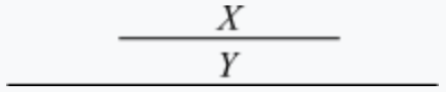
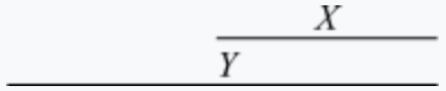
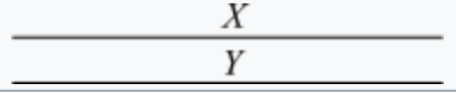
- CEP systems adds the ability to deploy *rules* that describe how composite events can be generated from primitive (or composite) ones
- Typical CEP rules search for ***sequences of events***
  - Raise C if A→B
- Time is a key aspect in CEP



Cugola, G., & Margara, A. (2012). **Processing flows of information: From data stream to complex event processing**. *ACM Computing Surveys (CSUR)*, *44*(3), 1-62.

CEP semantics

- subsets of Allen's Interval Algebra

Relation	Illustration	Interpretation
$X < Y$ $Y > X$		X takes place before Y
$X \mathbf{m} Y$ $Y \mathbf{mi} X$		X meets Y (*i* stands for *inverse*)
$X \mathbf{o} Y$ $Y \mathbf{oi} X$		X overlaps with Y
$X \mathbf{s} Y$ $Y \mathbf{si} X$		X starts Y
$X \mathbf{d} Y$ $Y \mathbf{di} X$		X during Y
$X \mathbf{f} Y$ $Y \mathbf{fi} X$		X finishes Y
$X = Y$		X is equal to Y

[src: https://en.wikipedia.org/wiki/Allen%27s_interval_algebra]

Detecting Languages

- Event Processing Language (EPL)

```
insert into alertIBM
select *
from pattern [
       every (
          StockTick(name="IBM",price>100)
          ->
          (StockTick(name="IBM",price<100)
               where timer:within(60 seconds))
     ];
```

Write a query which alerts on each IBM stock tick with a price greater then 100 followed by an IBM stock tick lower than 100 within 60 seconds

- Supported since 2006 Esper by EsperTech Inc. and Oracle CEP

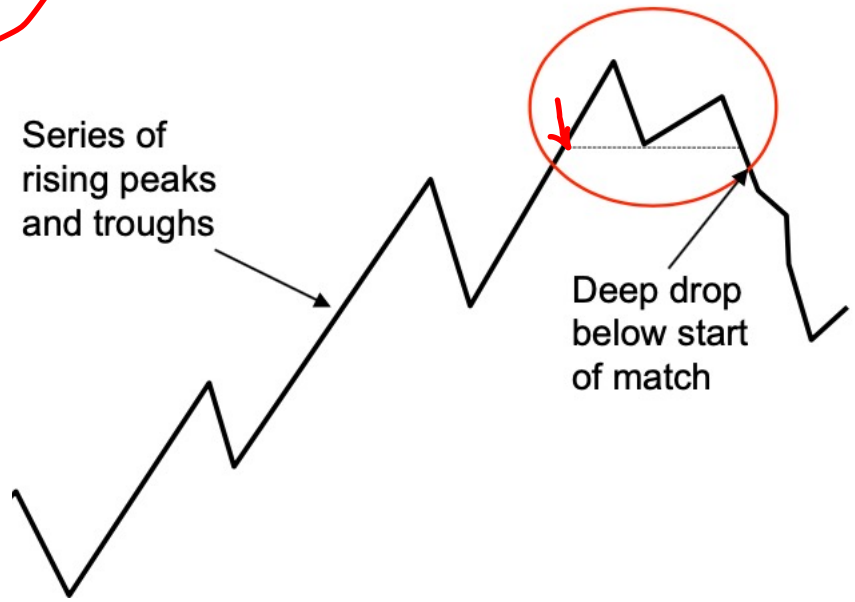
More Expressive Detecting Languages

Composite events *Simple events* *Regular expression*

```
1  stream<MatchT> Matches = MatchRegex(Quotes) {
2   param
3    pattern     : ". rise+ drop+ rise+ drop* deep";
4    partitionBy : symbol;
5    predicates  : {
6     rise = price>First(price)  && price>=Last(price),
7     drop = price>=First(price) && price<Last(price),
8     deep = price<First(price)  && price<Last(price) };
9   output
10   Matches : symbol=symbol, seqNum=First(seqNum),
11             count=Count(), maxPrice=Max(price);
12 }
```

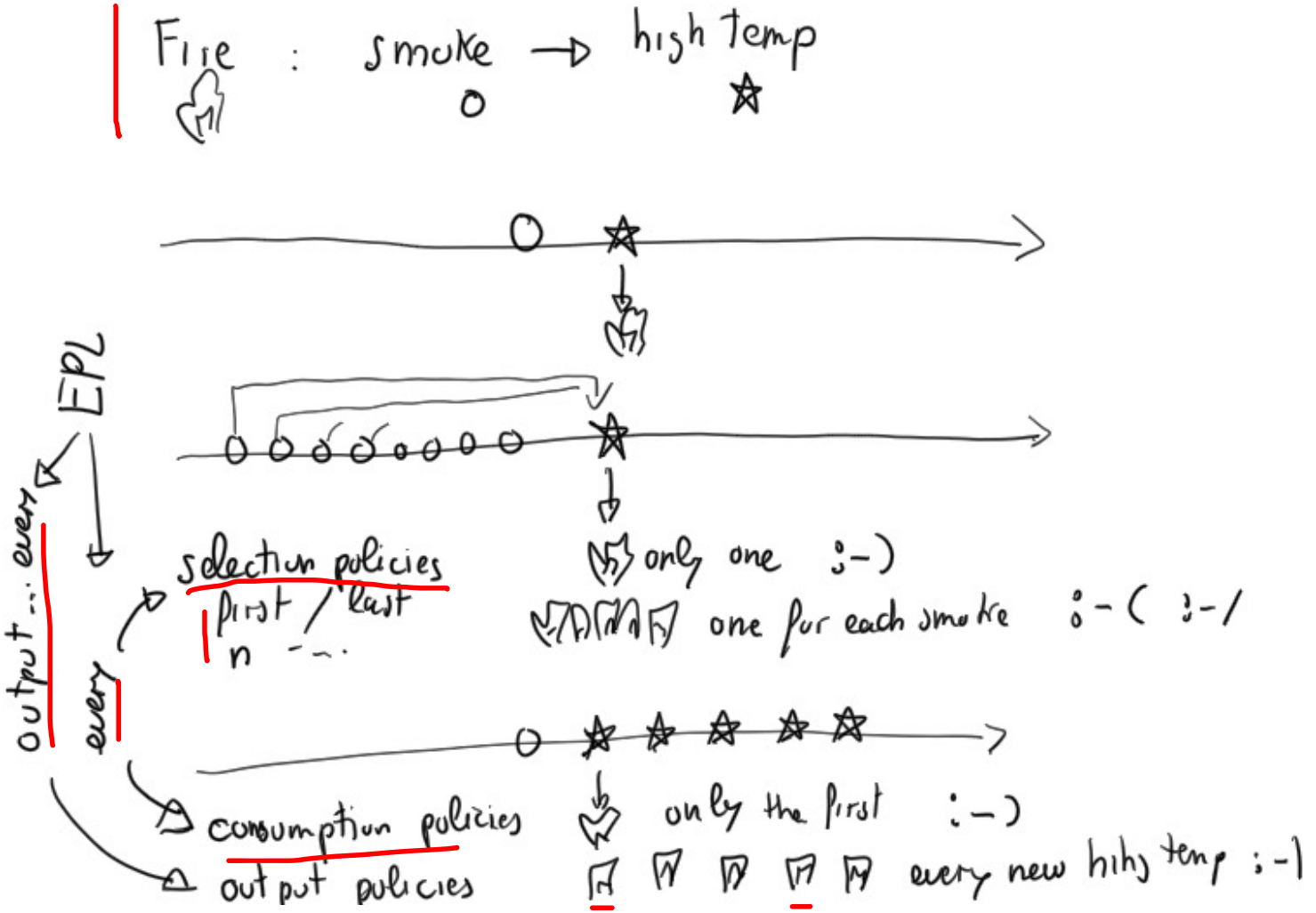
Key

Aggregation



➔ *Operator only, no extensions to SPL syntax*

Why can event-based systems fight the torrent effect?



Wrapping up


Kafka
horizontal
Spark
KSQLDB : ksql
COMPLEXITY
DSMS
Simple
pub-sub
MQTT
Complex
ABILITY TO SCALE
vertical
Esper : EPL

Thank you for your attention!

Questions?

Credits

- These slides are partially based on
  - "A modeling framework for DSMS and CEP" by G. Cugola and A. Margara presented in the PhD course on "Stream and complex event processing" offered by Politecnico di Milano in 2015.
    - http://www.streamreasoning.org/courses/scep2015
  - "Tutorial: Stream Processing Languages" by Martin Hirzel, IBM Research AI. 1 November 2017 Dagstuhl Seminar on Big Stream Processing Systems
    - https://materials.dagstuhl.de/files/17/17441/17441.MartinHirzel1.Slides.pdf
  - "The Death and Rebirth of the Event Driven Architecture" by Jay Kreps, Confluent, Kafka Summit 2018
    - https://www.confluent.io/kafka-summit-london18/keynote-the-death-and-rebirth-of-the-event-driven-architecture
  - “Time Series Databases” by Dmitry Namiot
    - https://www.slideshare.net/coldbeans/on-timeseries-databases
  - “Fractal Tree Indexes : From Theory to Practice” by Tim Callaghan
    - https://www.slideshare.net/tmcallaghan/20131112-plukfractaltreestheorytopractice

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