

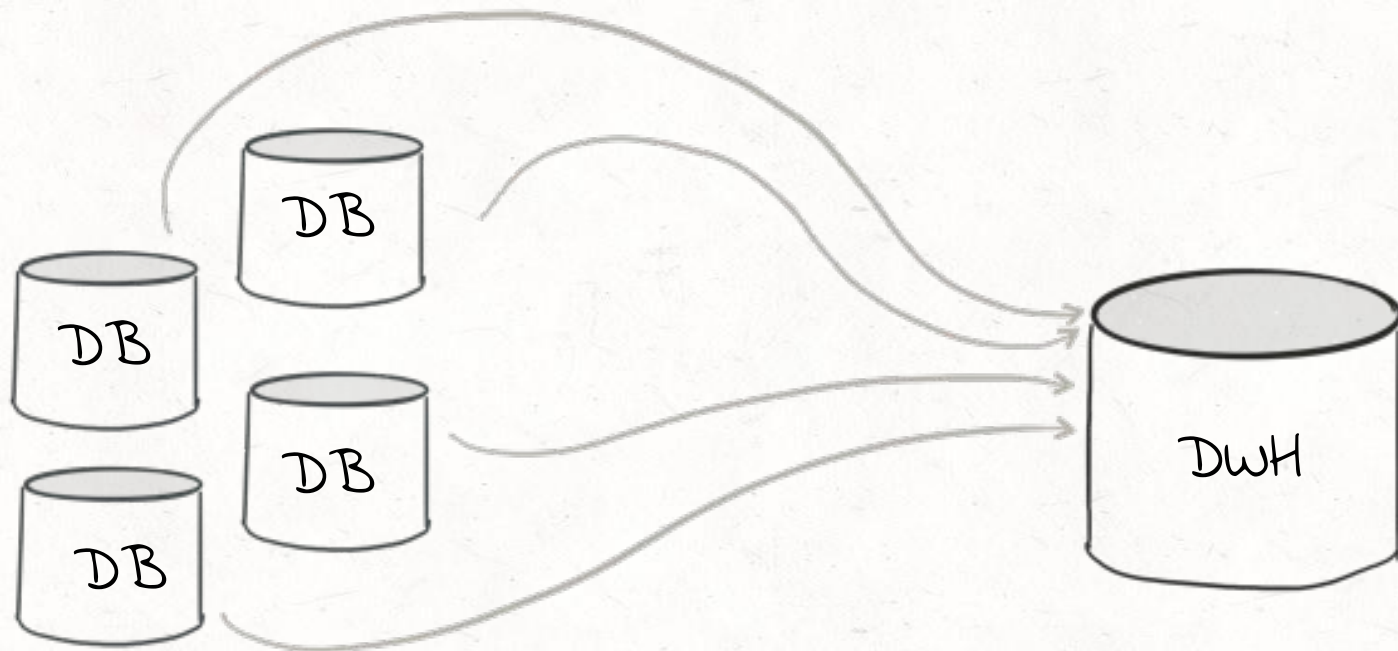
# ETL IS DEAD; LONG-LIVE STREAMS

Neha Narkhede,  
Co-founder & CTO, Confluent

“

Data and data systems have really  
changed in the past decade

# OLD WORLD: TWO POPULAR LOCATIONS FOR DATA



Operational databases

Relational data warehouse

“

Several recent data trends are driving a dramatic change in the ETL architecture



”

#1: Single-server databases are replaced  
by a myriad of distributed data  
platforms that operate at company-wide  
scale

”

#2: Many more types of data sources  
beyond transactional data - logs, sensors,  
metrics...

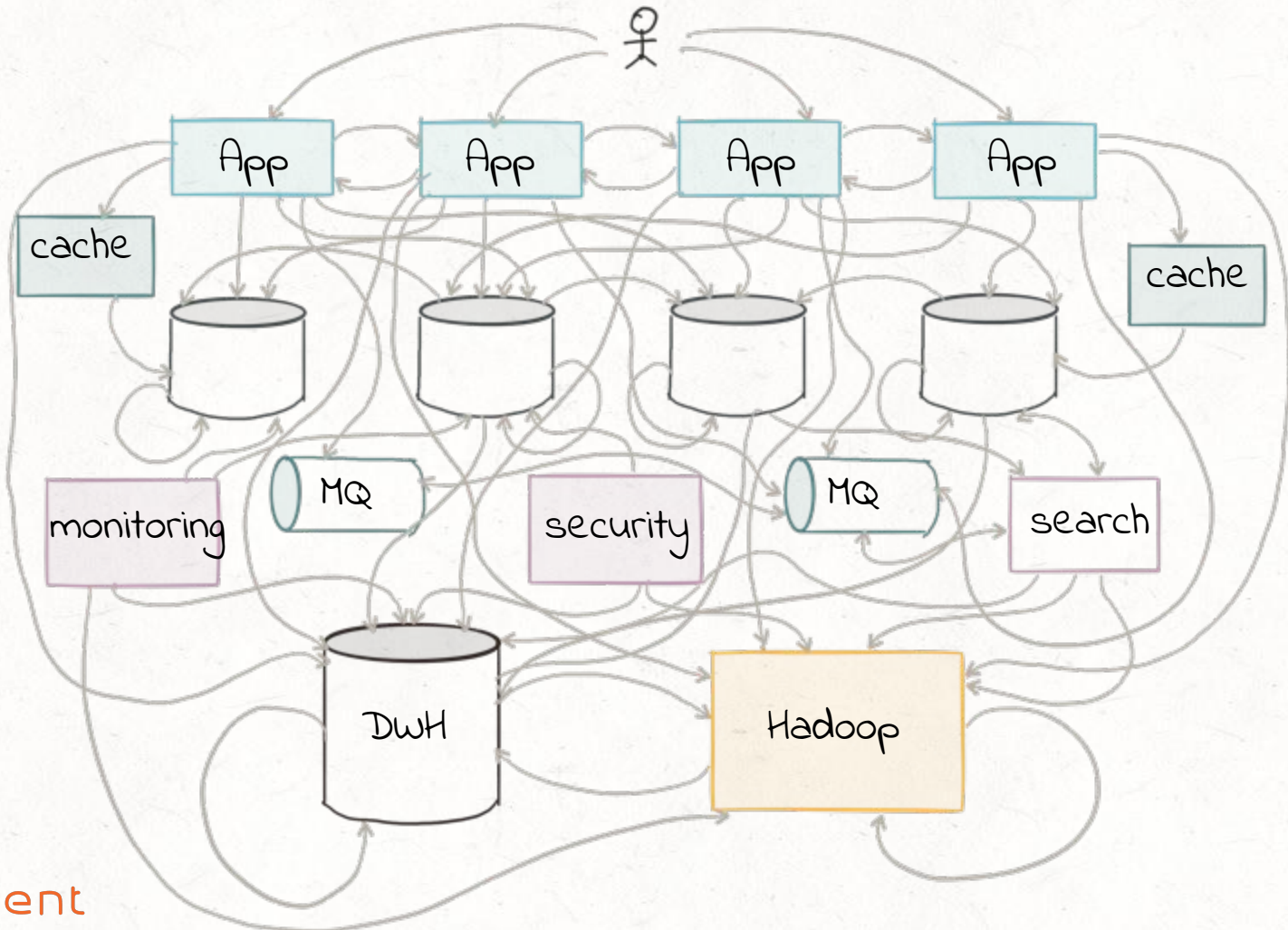
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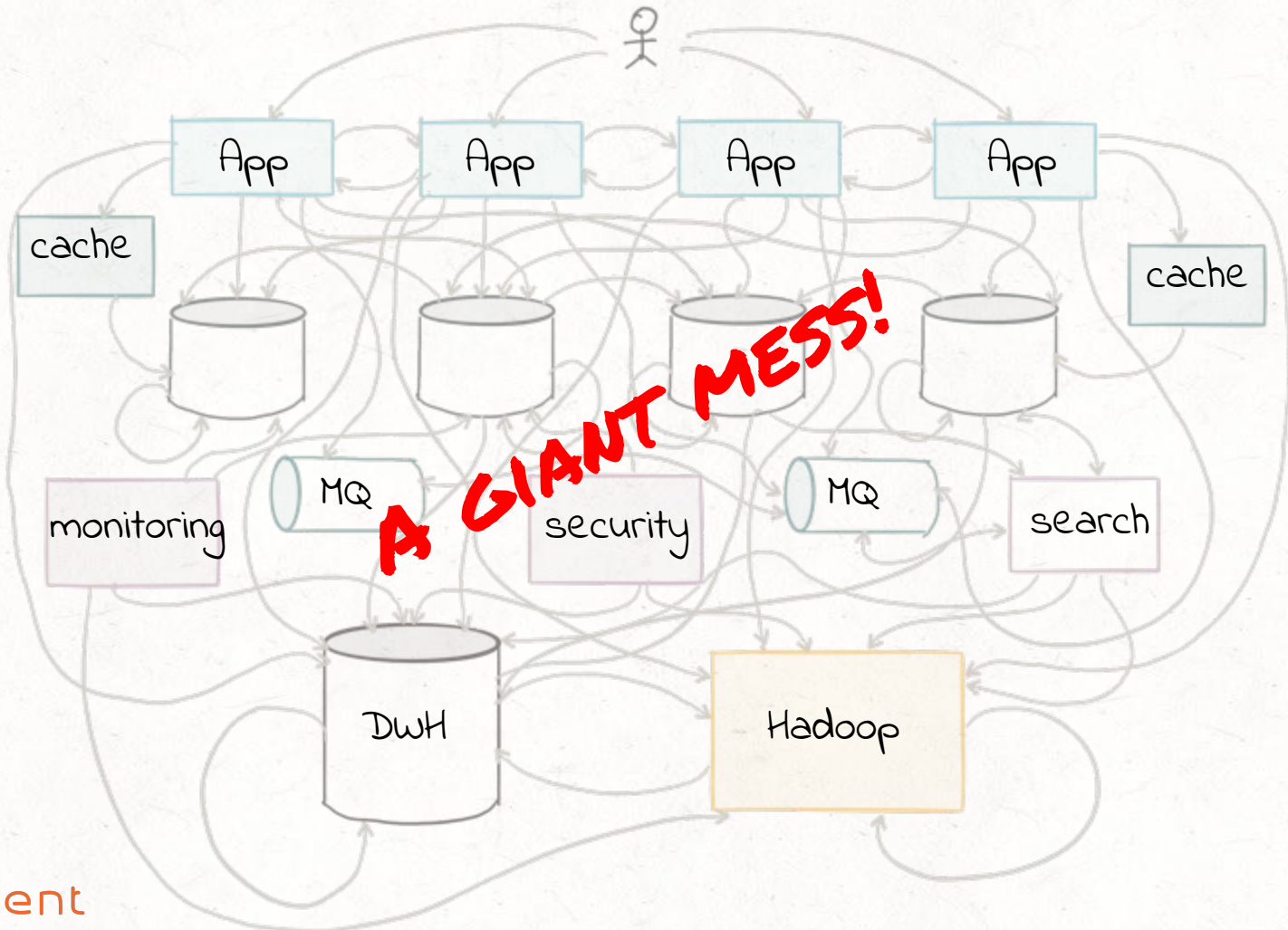
#3: Stream data is increasingly ubiquitous; need for faster processing than daily

“

The end result? This is what data integration ends up looking like in practice

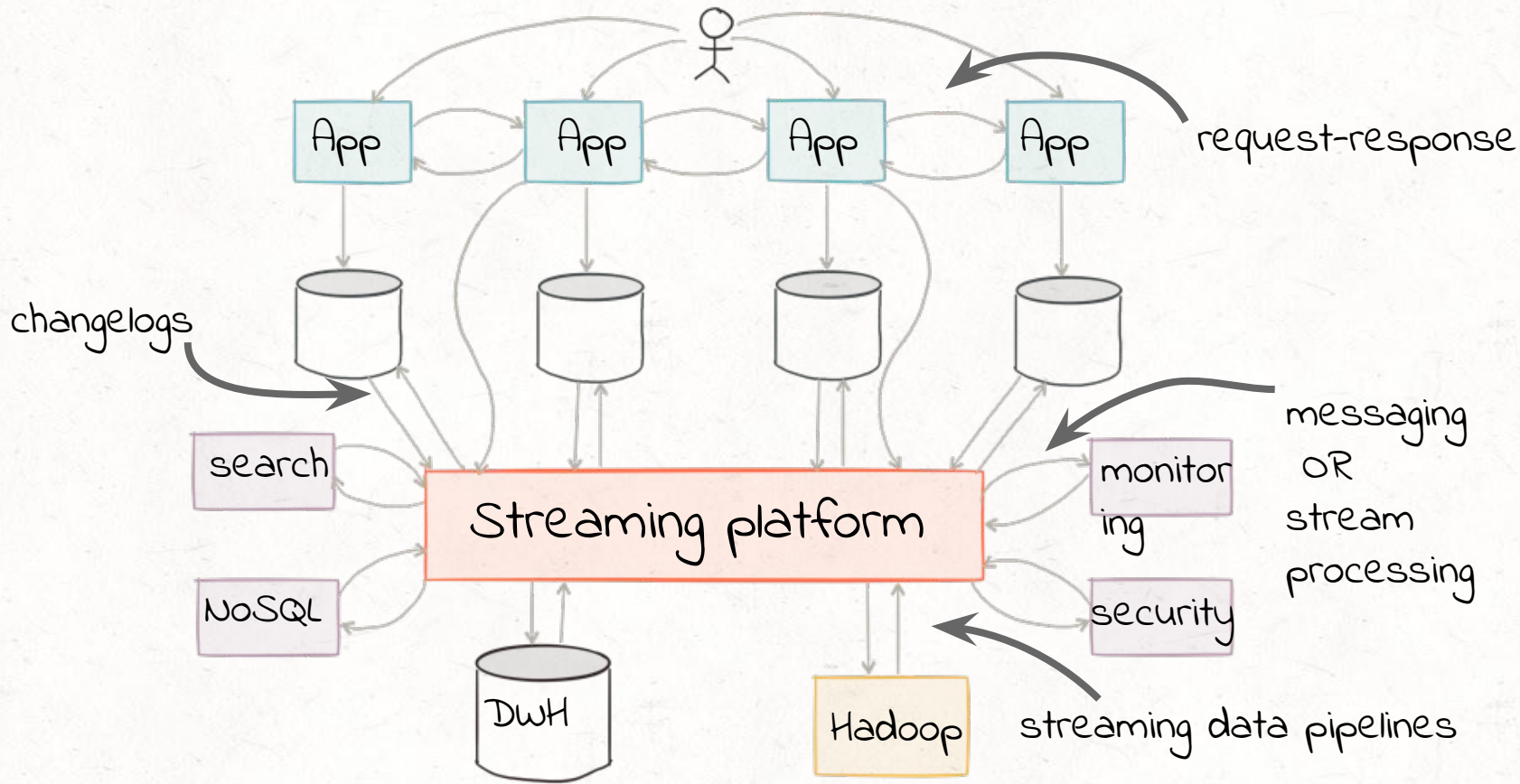






“

we will see how transitioning to streams  
cleans up this mess and works towards...





A large, irregular orange watercolor splash is centered on the page, serving as a background for the title text.

# A SHORT HISTORY OF DATA INTEGRATION

“

Surfaced in the 1990s in retail organizations for analyzing buyer trends



**Extract** data from databases

**Transform** into destination warehouse schema

**Load** into a central data warehouse

“

BUT ... ETL tools have been around for a long time, data coverage in data warehouses is still low! WHY?





**ETL HAS DRAWBACKS**

”

#1: The need for a *global schema*

”

#2: Data cleansing and curation is  
manual and fundamentally **error-prone**

”

#3: Operational cost of ETL is high; it is slow; time and **resource intensive**



”

#4: **ETL** tools were built to narrowly focus on connecting databases and the data warehouse in a **batch** fashion

“

Early take on real-time ETL

=

Enterprise Application Integration (EAI)

”

**EAI:** A different class of data integration technology for connecting applications in real-time

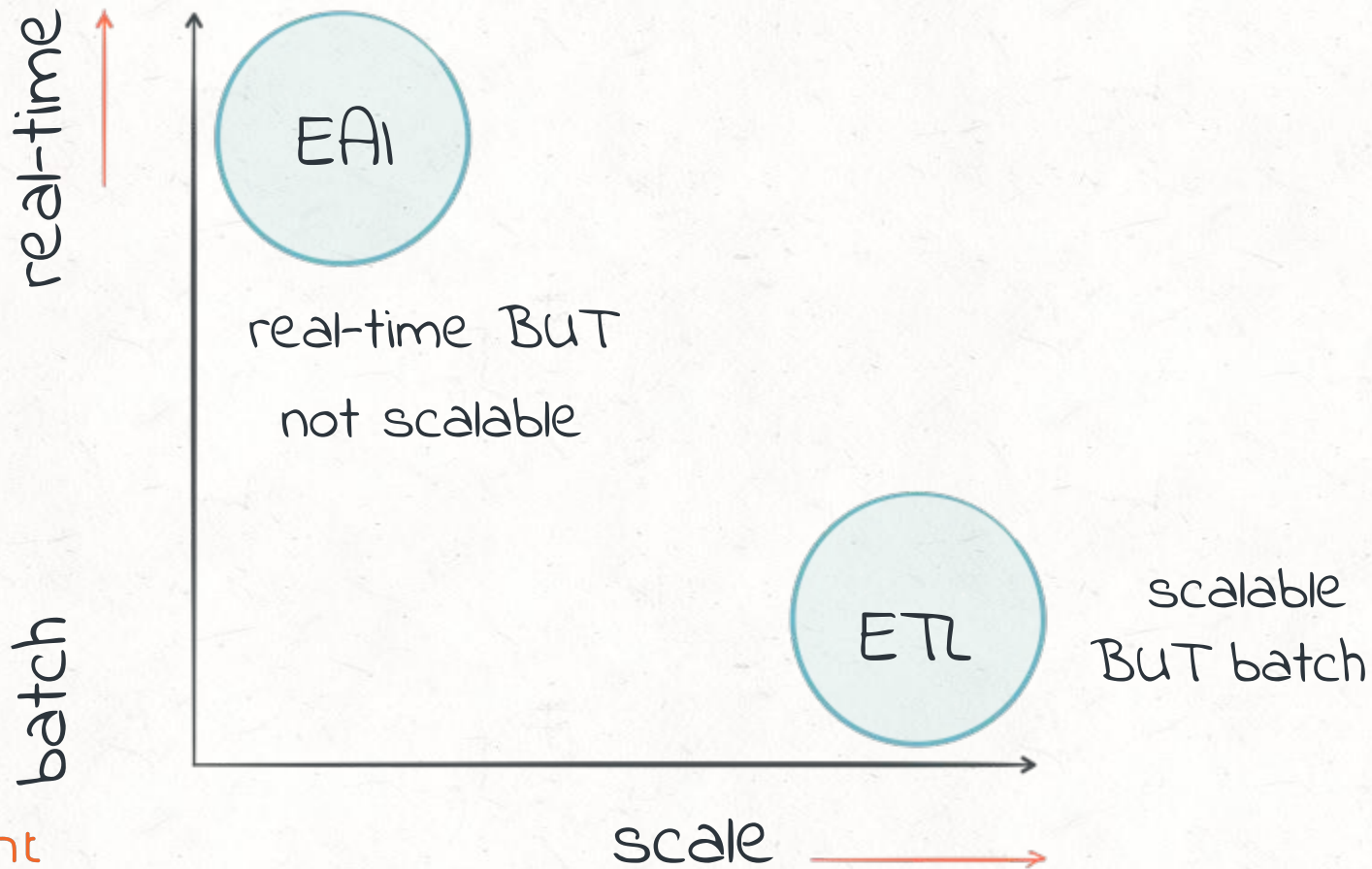
“

EAI employed Enterprise Service Buses  
and MQs; weren't scalable



**ETL AND EAI ARE  
OUTDATED!**

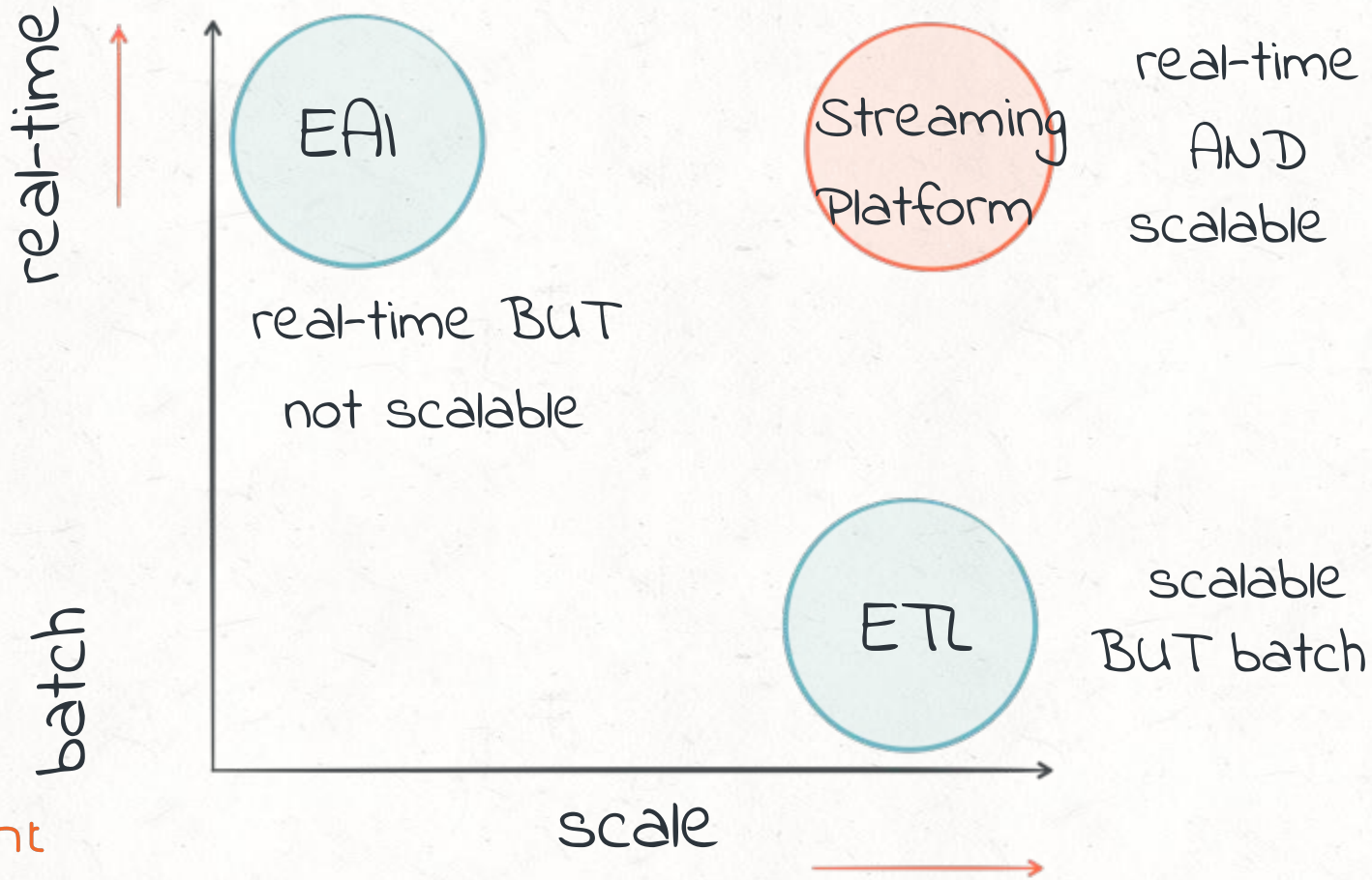
# OLD WORLD: SCALE OR TIMELY DATA, PICK ONE



“

Data integration and ETL in the modern world need a complete revamp

# NEW WORLD: STREAMING, REAL-TIME AND SCALABLE





“

Modern streaming world has new set of  
**requirements** for data integration

”

#1: Ability to process high-volume and high-diversity data

“  
#2 Real-time from the grounds up; a  
fundamental transition to  
event-centric thinking

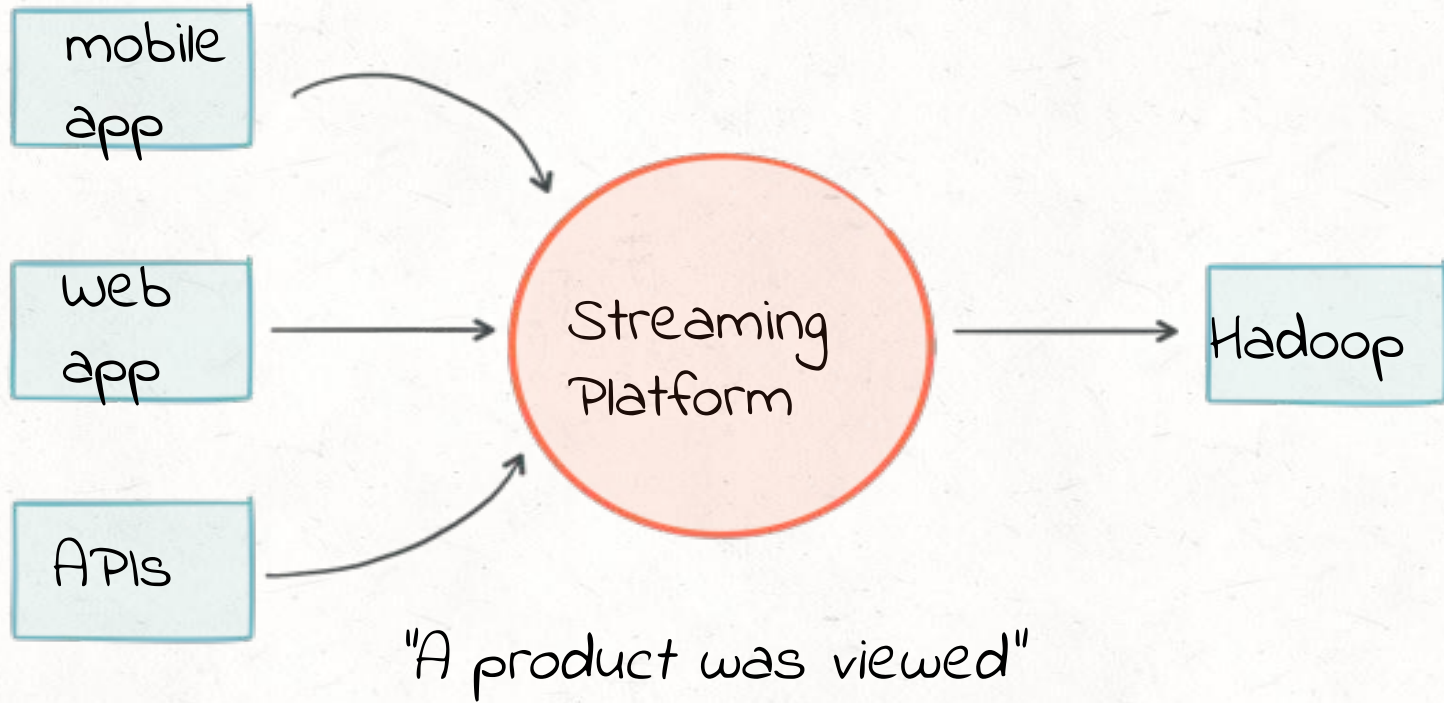
# Event-Centric Thinking



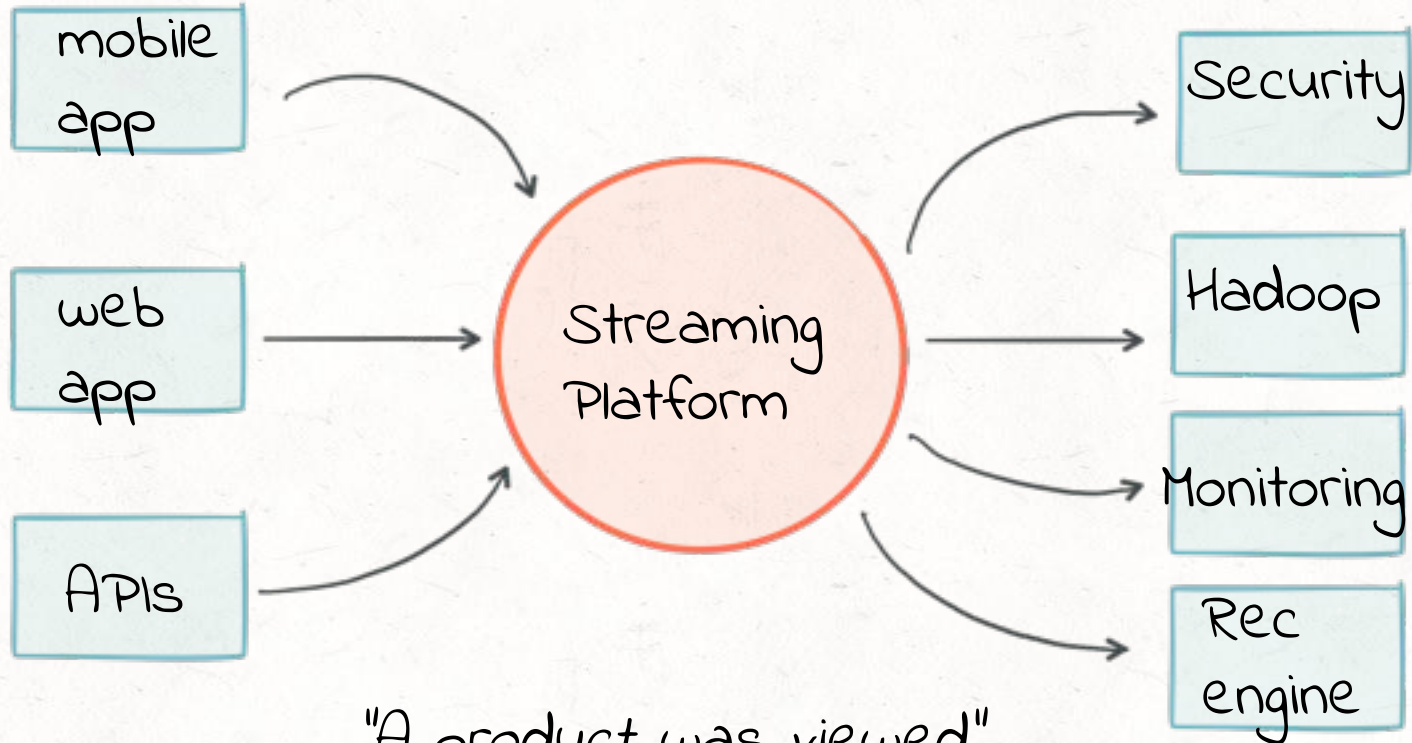
"A product was viewed"



# Event-Centric Thinking

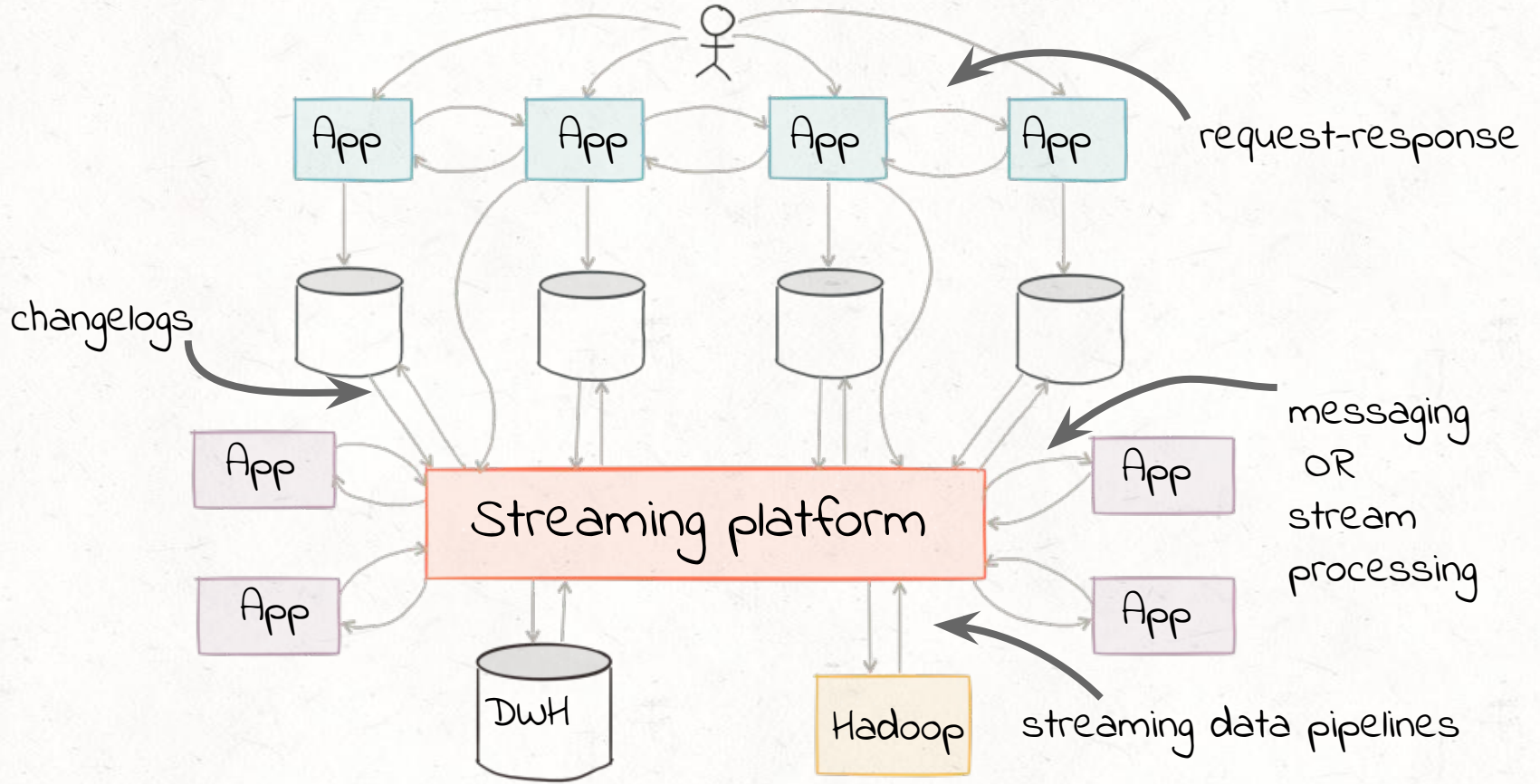


# Event-Centric Thinking



“

Event-centric thinking, when applied at a company-wide scale, leads to this simplification ...





”

#3: Enable forward-compatible data architecture; the ability to add more applications that need to process the same data ... differently

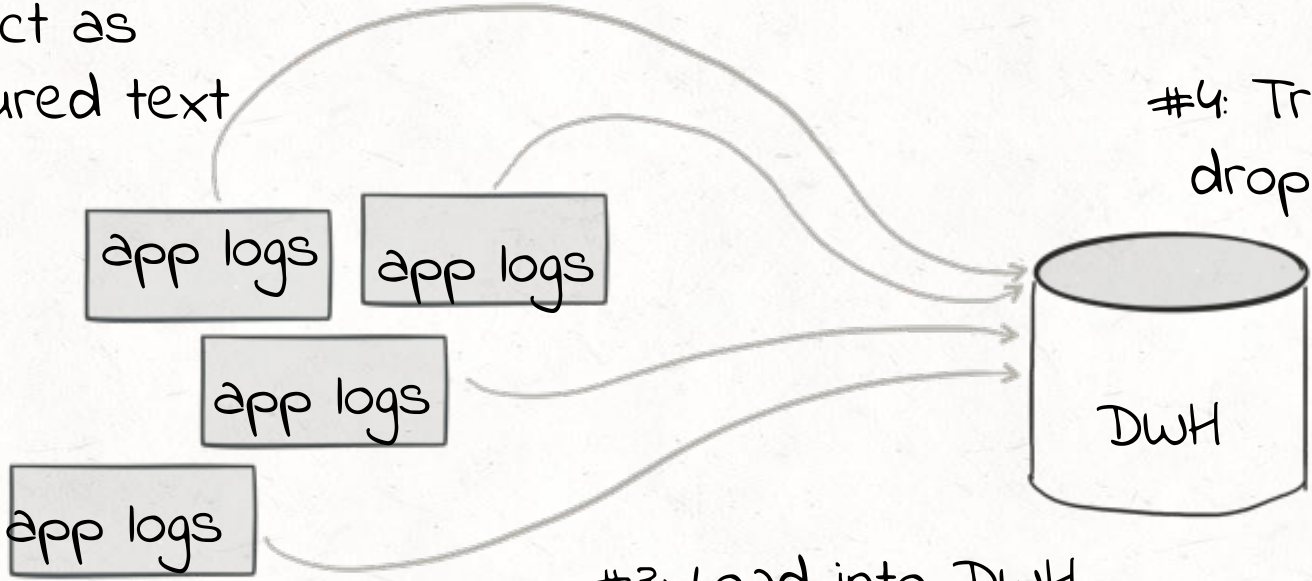
”

To enable forward compatibility, redefine  
the T in ETL:

Clean data in; Clean data out

#2: Transform1 = data cleansing  
= "what is a product view"

#1: Extract as  
unstructured text



#4: Transform2 =  
drop PII fields"

#3: Load into DWH

#2: Transform1 = data cleansing = "what is a product view"

#1: Extract as unstructured text

#3: Load cleansed data

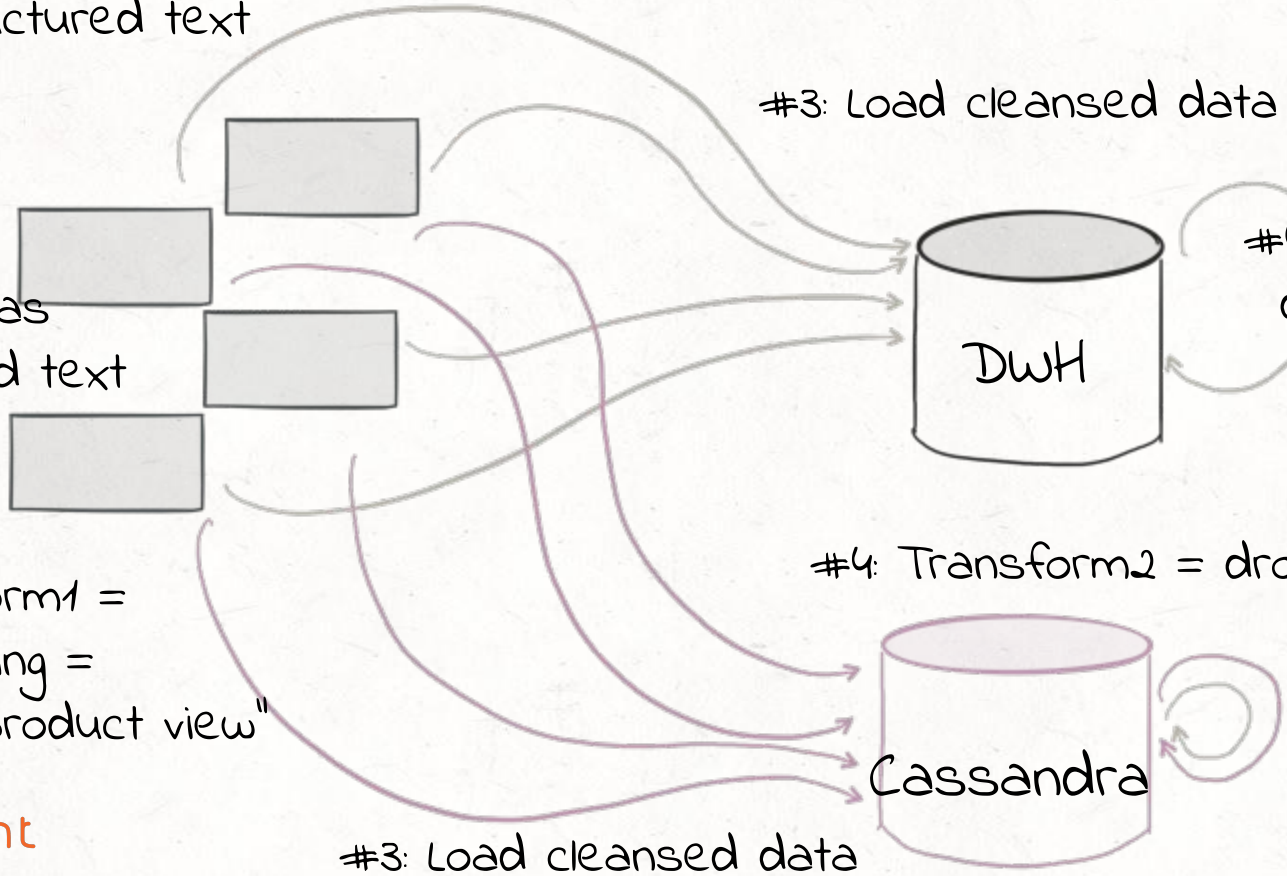
#4: Transform2 = drop PII fields"

#1: Extract as unstructured text again

#2: Transform1 = data cleansing = "what is a product view"

#4: Transform2 = drop PII fields"

#3: Load cleansed data

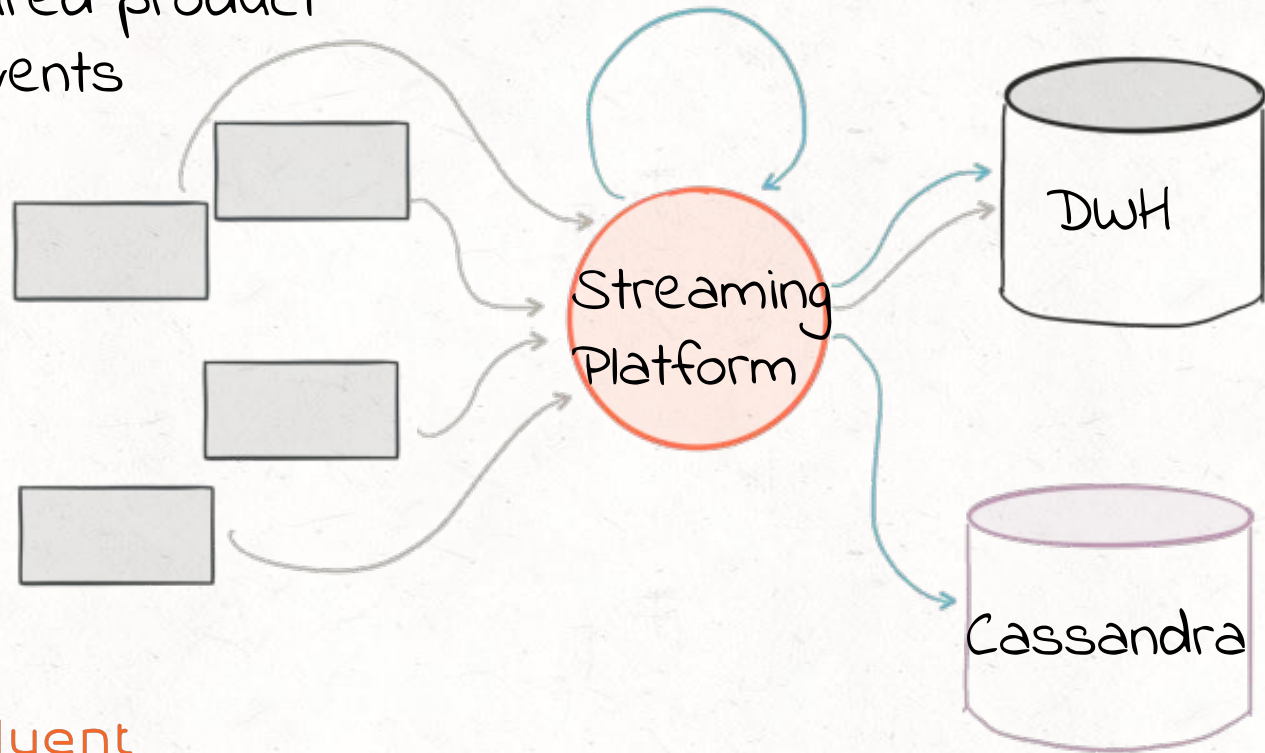




#1: Extract as structured product view events

#2: Transforms = drop PII fields"

#4.1 Load product view stream



#4.2 Load filtered product view stream

#4: Load filtered product view stream

“

To enable forward compatibility, redefine

the T in ETL:

Data transformations, not data cleansing!

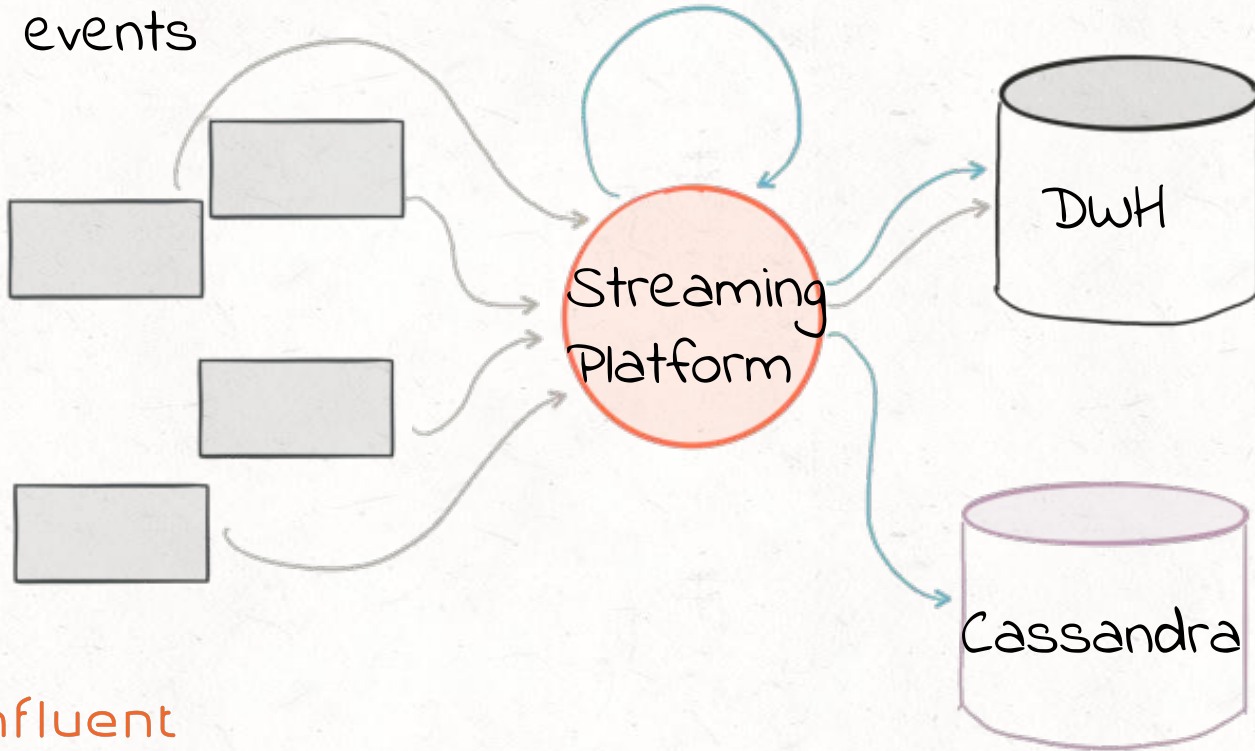
#1: Extract **once** as structured product view events

#2: Transform **once** = drop PII fields" and enrich with product metadata

#4.1: Load product views stream

#4.2: Load filtered and enriched product views stream

#4: Load filtered and enriched product views stream



”

Forward compatibility =  
Extract clean-data once; Transform many  
different ways before Loading into respective  
destinations ... as and when required



”

In summary, needs of modern data  
integration solution?

Scale, diversity, latency and forward  
compatibility

# REQUIREMENTS FOR A MODERN STREAMING DATA INTEGRATION SOLUTION

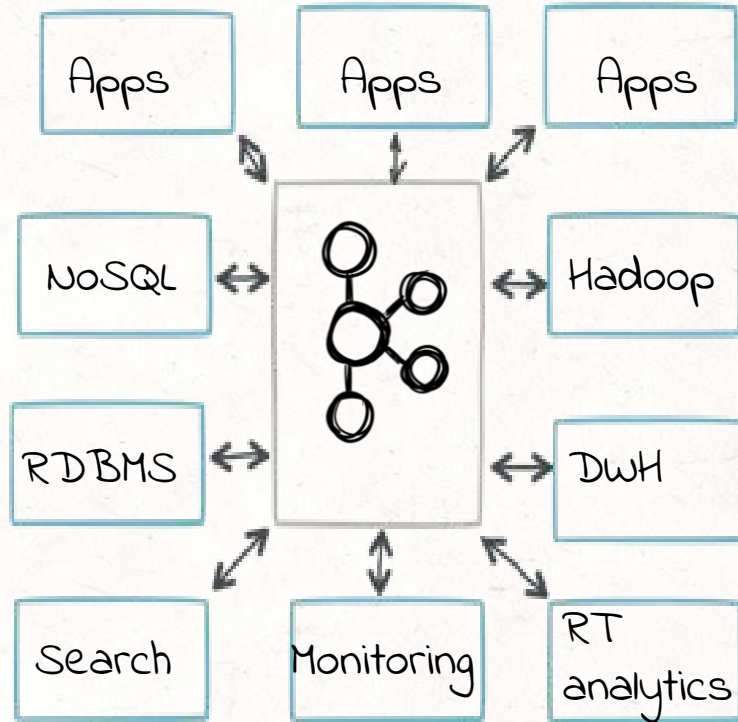
- Fault tolerance
- Parallelism
- Latency
- Delivery semantics
- Operations and monitoring
- Schema management

# DATA INTEGRATION: PLATFORM VS TOOL

Central, reusable  
infrastructure for  
many use cases

One-off, non-reusable  
solution for a  
particular use case

# NEW SHINY FUTURE OF ETL: A STREAMING PLATFORM





“

Streaming platform serves as the central nervous system for a company's data in the following ways ...

“  
#1: Serves as the **real-time**, scalable  
**messaging bus** for applications; no  
EAI

”

#2: Serves as the **source-of-truth** pipeline for feeding all data processing destinations; Hadoop, DWH, NoSQL systems and more



”

#3: Serves as the **building block** for  
stateful **stream processing**  
microservices



”

Streaming

~~Batch data integration~~

”

Streaming  
~~Batch ETL~~

a short history of data integration

drawbacks of ETL

needs and requirements for a streaming platform

new, shiny future of ETL: a streaming platform

what does a streaming platform look like and how  
it enables Streaming ETL?

# APACHE KAFKA: A DISTRIBUTED STREAMING PLATFORM







**APACHE KAFKA 6 YEARS  
AGO**



> 1,400,000,000,000  
messages processed / day

# NOW ADOPTED AT 1000S OF COMPANIES WORLDWIDE

NETFLIX

intuit.

  
Pinterest

Goldman  
Sachs

 airbnb

ebay



  
Adobe

box

yelp 

 Square

  
CISCO.

dish  
NETWORK

salesforce

 Cerner

  
WIKIPEDIA  
The Free Encyclopedia



PayPal™

  
verizon

“

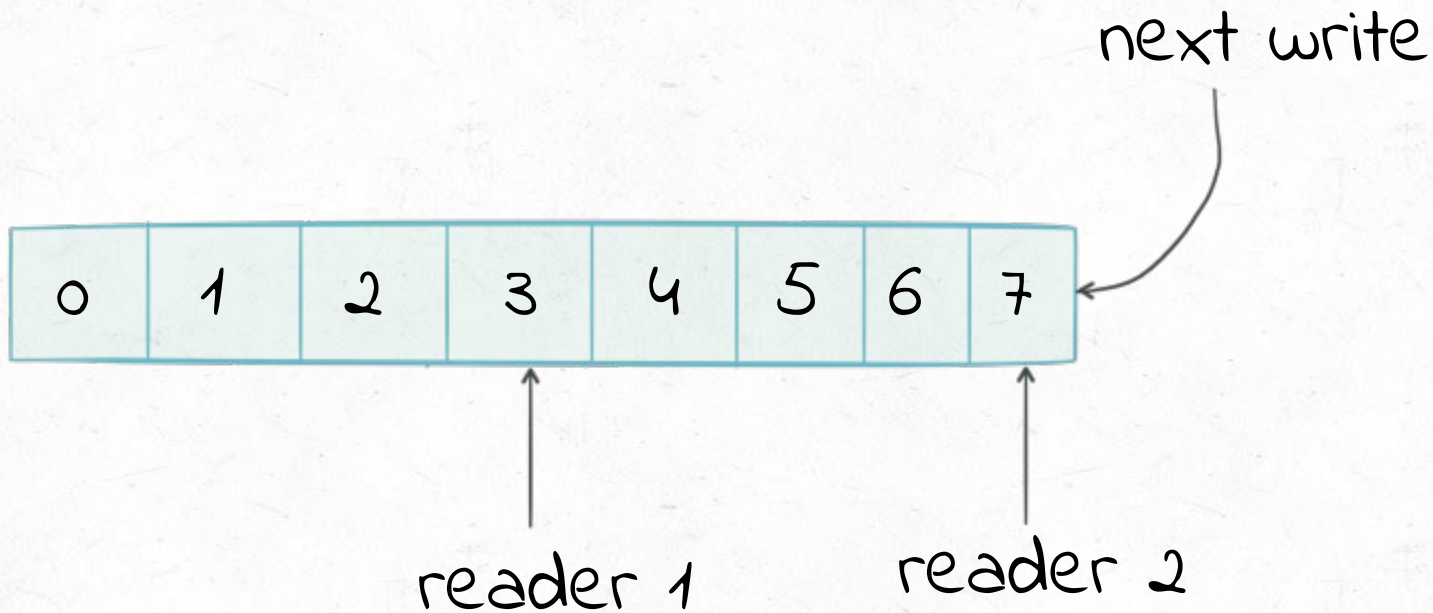
what role does Kafka play in the new shiny future for data integration?



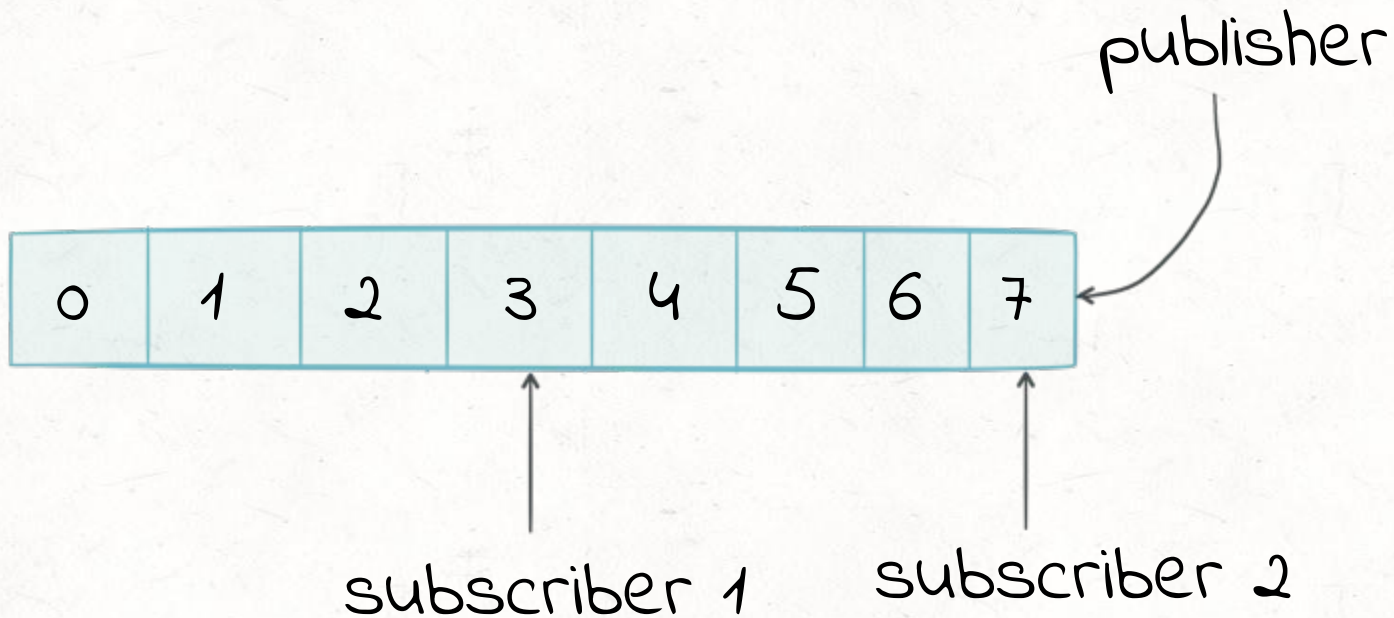
”

#1: Kafka is the de-facto storage of choice for stream data

# THE LOG



# THE LOG + PUB-SUB

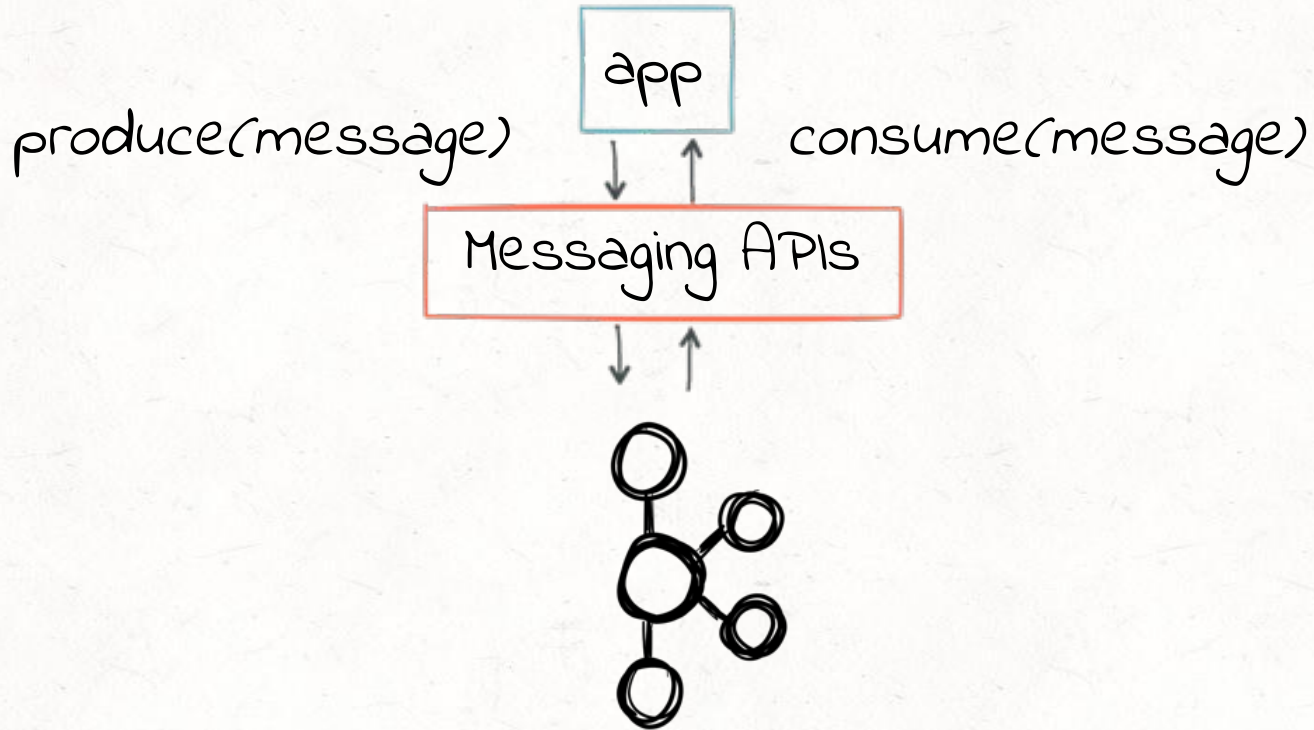


”

#2: Kafka offers a scalable  
messaging backbone for application  
integration



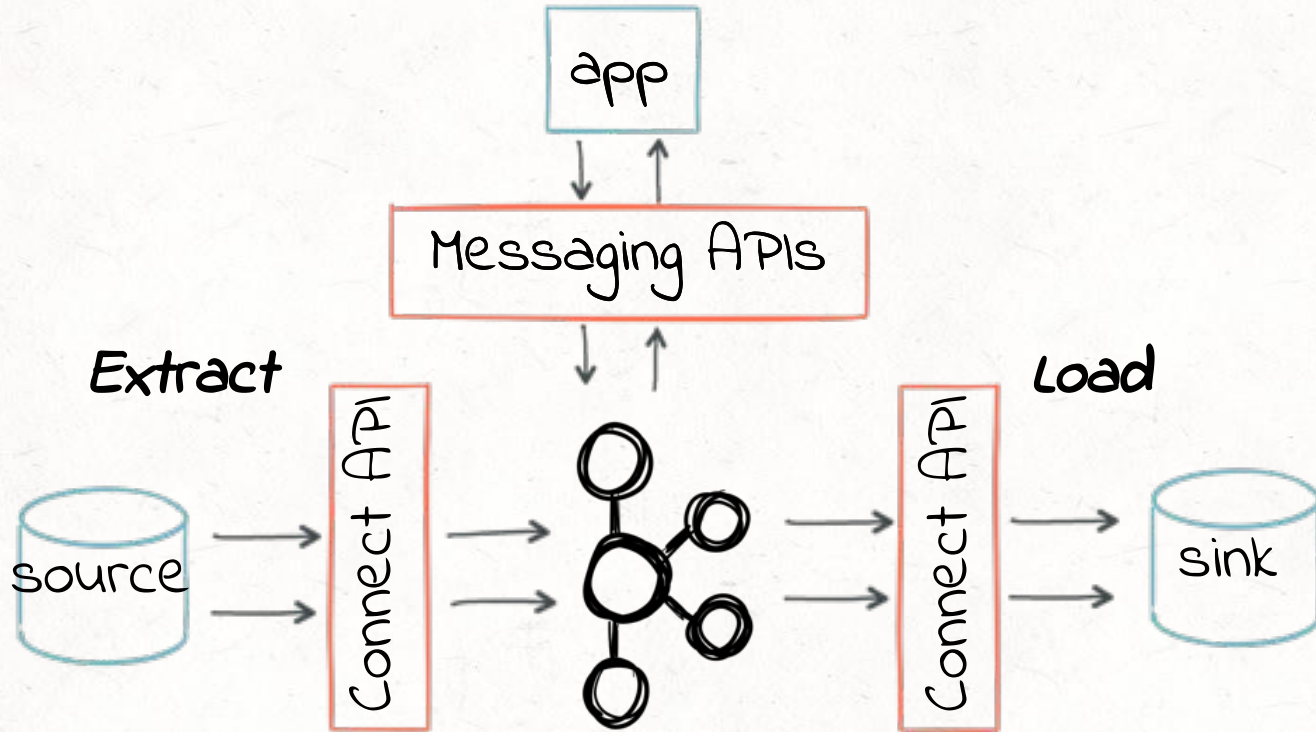
# KAFKA MESSAGING APIS: SCALABLE EAI



”

#3: Kafka enables building streaming data pipelines (E & L in ETL)

# KAFKA'S CONNECT API: STREAMING DATA INGESTION

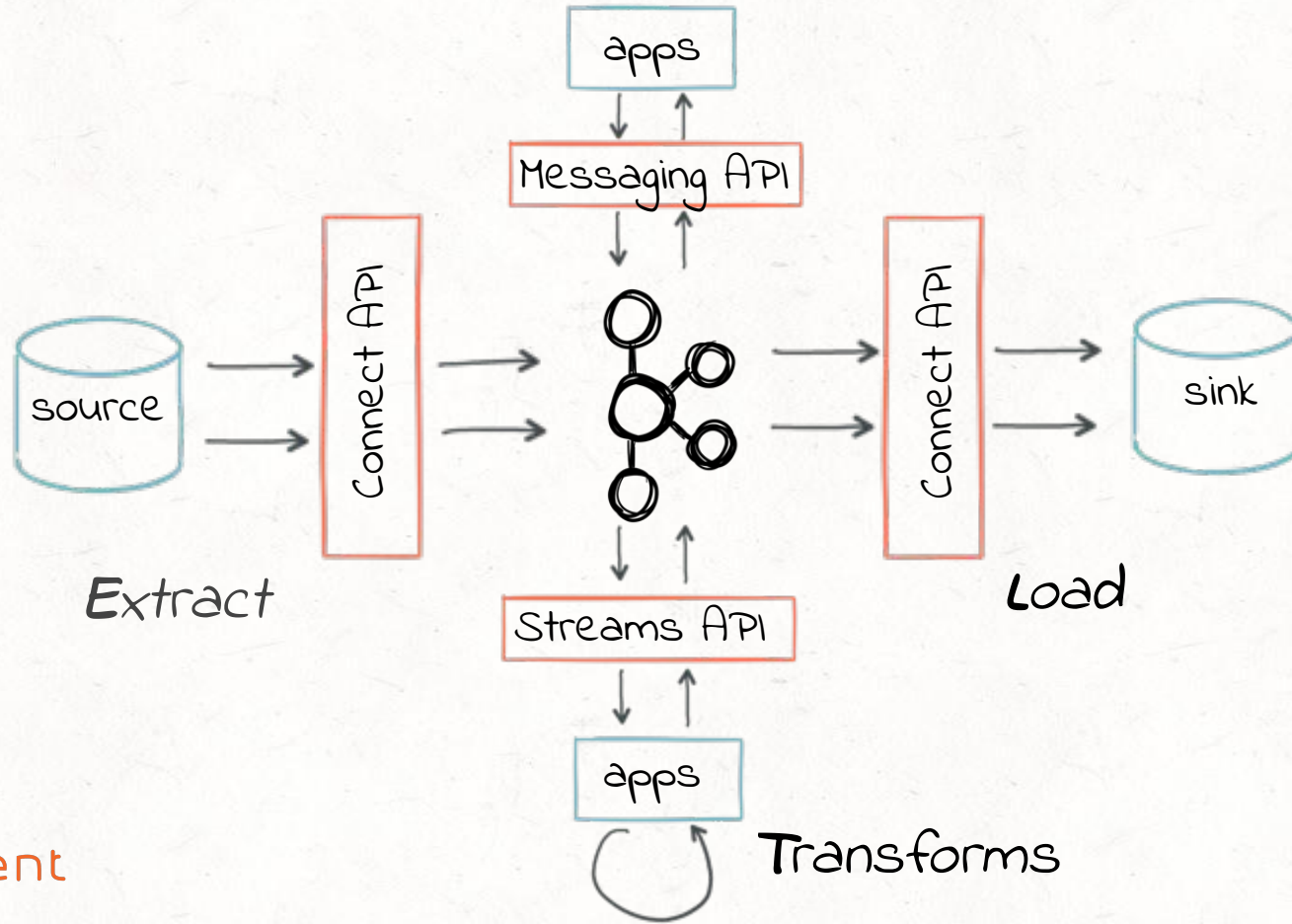


”

#4: Kafka is the basis for stream processing and transformations

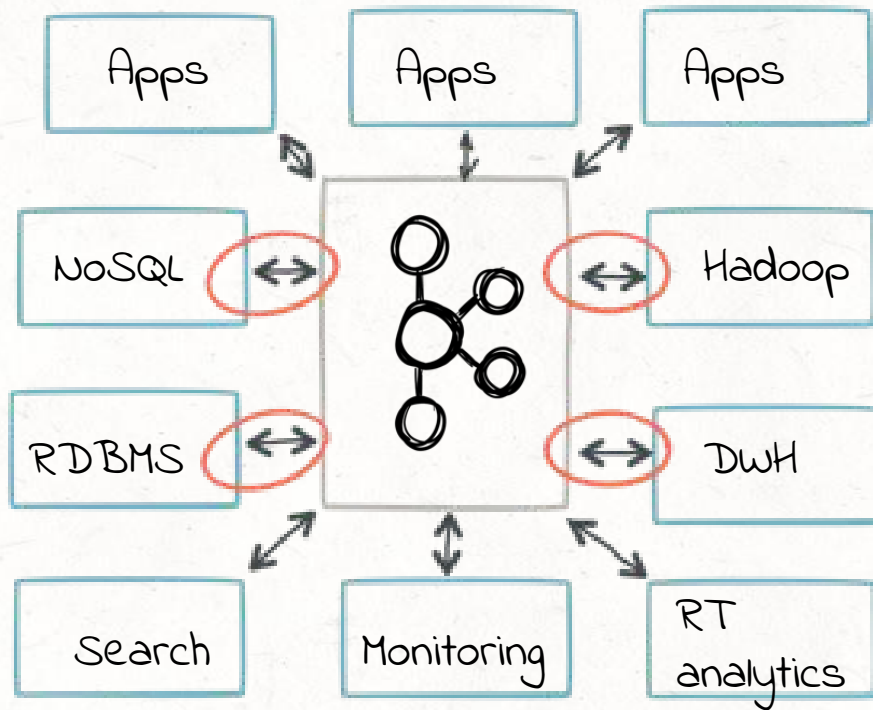


# KAFKA'S STREAMS API: STREAM PROCESSING (TRANSFORMS)

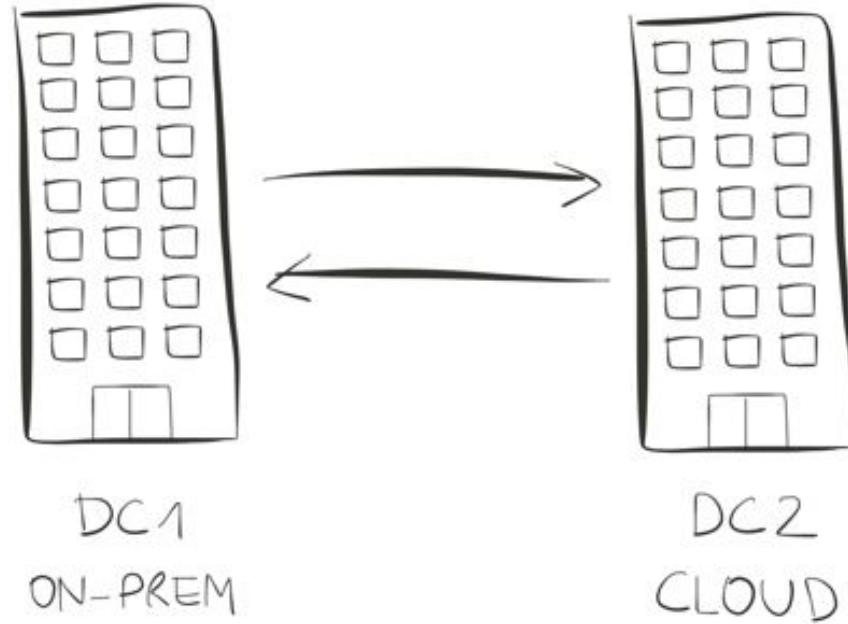


**KAFKA'S CONNECT API  
=  
E AND L IN STREAMING ETL**

# CONNECTORS!

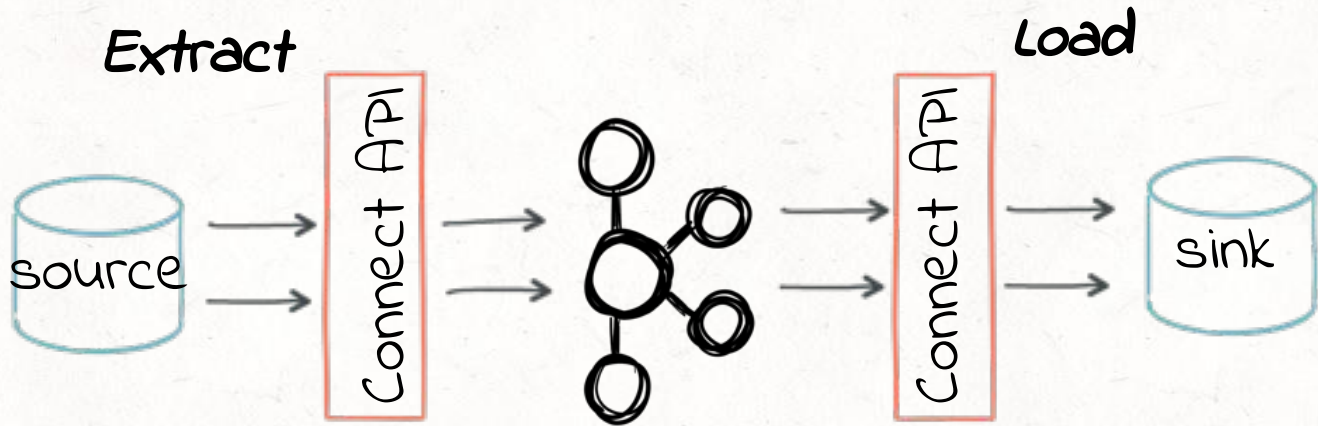


# HOW TO KEEP DATA CENTERS IN-SYNC?

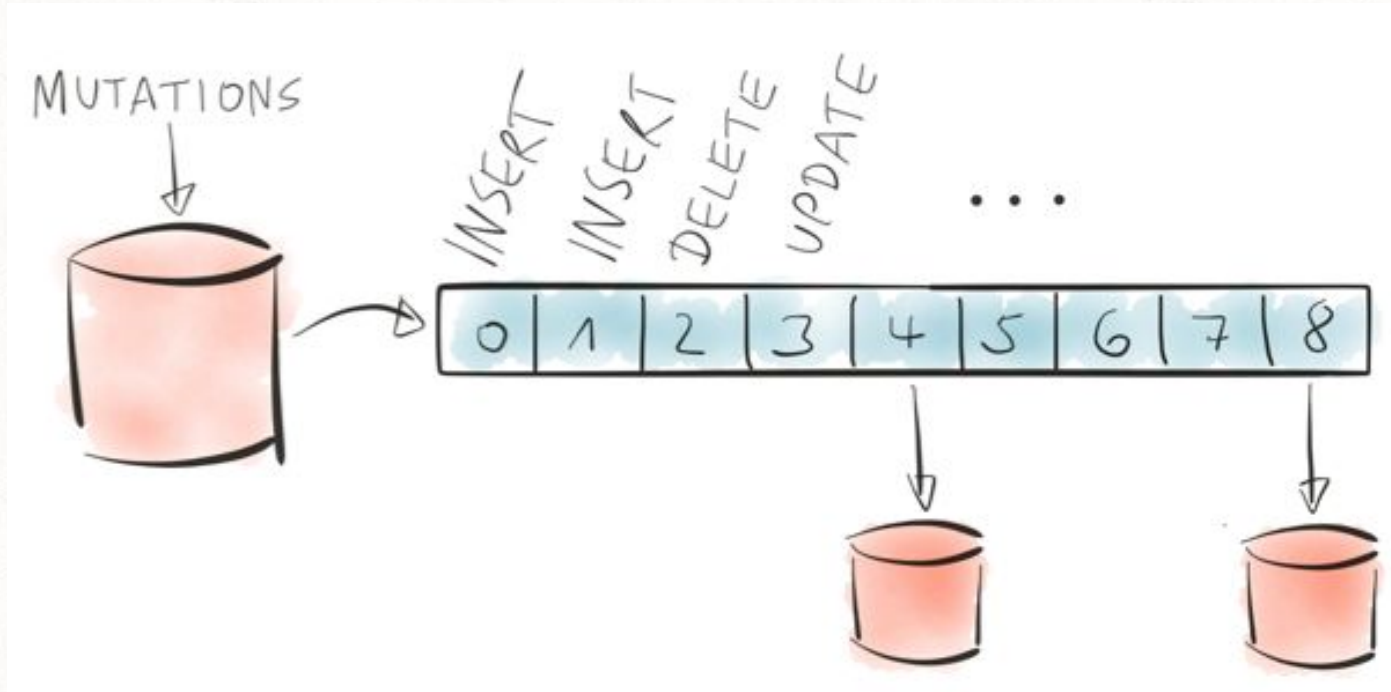




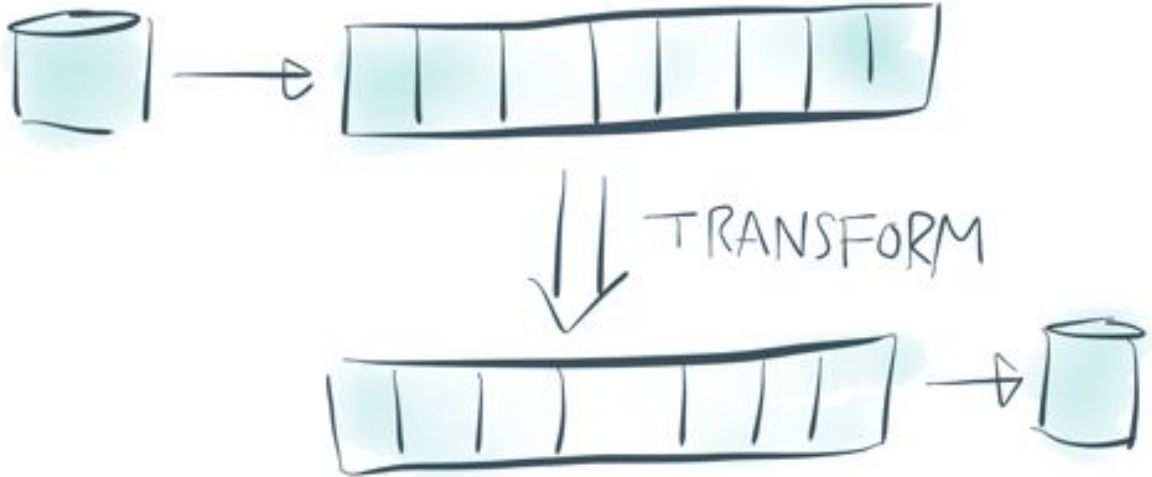
# SOURCES AND SINKS



# CHANGELOGS



# TRANSFORMING CHANGELOGS

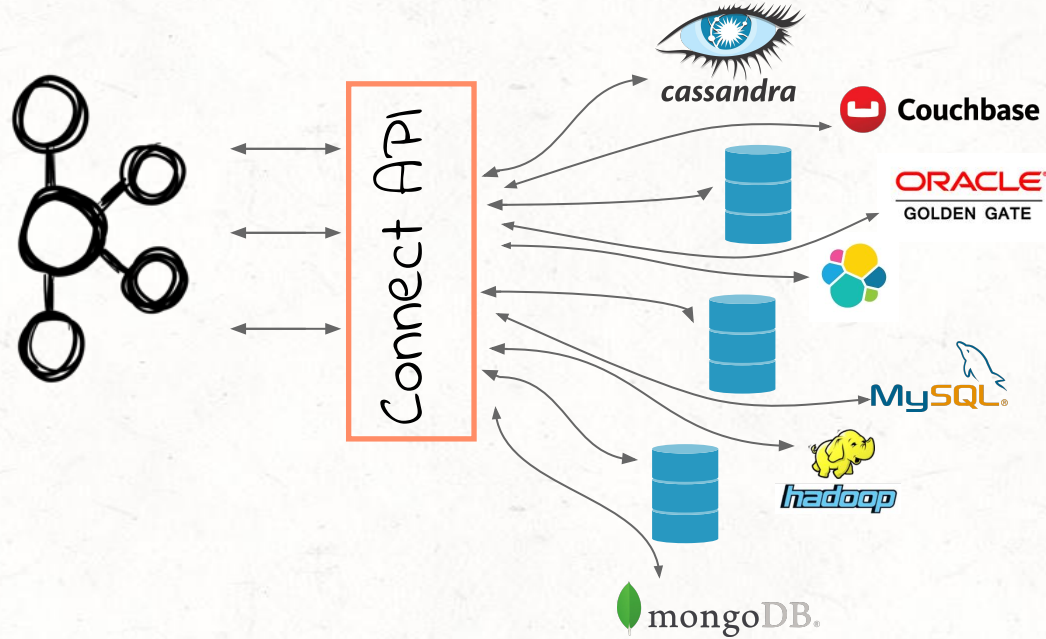


# KAFKA'S CONNECT API = CONNECTORS MADE EASY!

- **Scalability:** Leverages Kafka for scalability
- **Fault tolerance:** Builds on Kafka's fault tolerance model
- **Management and monitoring:** one way of monitoring all connectors
- **Schemas:** offers an option for preserving schemas from source to sink



# KAFKA ALL THE THINGS!



**KAFKA'S STREAMS API**  
**=**  
**THE T IN STREAMING ETL**

“

Stream processing =  
**transformations** on stream data

## 2 VISIONS FOR STREAM PROCESSING

Real-time Mapreduce VS Event-driven microservices



## 2 VISIONS FOR STREAM PROCESSING

Real-time Mapreduce VS Event-driven microservices

- Central cluster
- Custom packaging, deployment & monitoring
- Suitable for analytics-type use cases

- Embedded library in any Java app
- Just Kafka and your app
- Makes stream processing accessible to any use case

# VISION 1: REAL-TIME MAPREDUCE



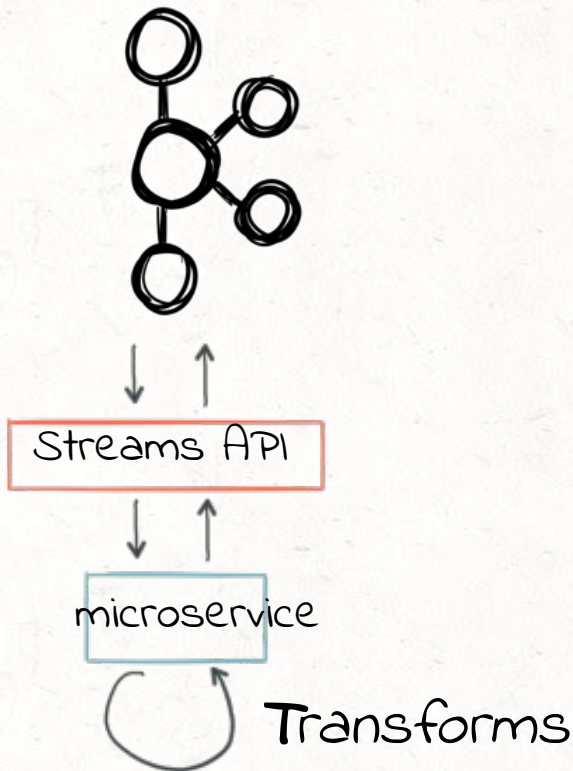
**STORM**

**Spark**  
*Streaming*



**Flink**

# VISION 2: EVENT-DRIVEN MICROSERVICES => KAFKA'S STREAMS API



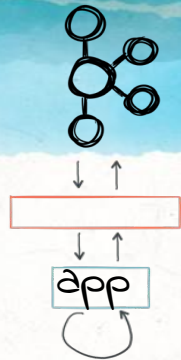
“

Kafka's Streams API = Easiest way to do  
stream processing using Kafka



”

#1: Powerful and lightweight Java library; need just Kafka and your app



”

#2: Convenient DSL with all sorts of operators: `join()`, `map()`, `filter()`, windowed aggregates etc

# WORD COUNT PROGRAM USING KAFKA'S STREAMS API

```
KStreamBuilder builder = new KStreamBuilder();  
KStream<String, String> textLines = builder.stream(stringDeserializer, stringDeserializer, "TextLinesTopic");  
  
KStream<String, Long> wordCounts = textLines  
    .flatMapValues(value -> Arrays.asList(value.toLowerCase().split("\\W+")))  
    .map((key, value) -> new KeyValue<>(value, value))  
    .countByKey(stringSerializer, longSerializer, stringDeserializer, longDeserializer, "Counts")  
    .toStream();  
wordCounts.to("WordsWithCountsTopic", stringSerializer, longSerializer);  
  
KafkaStreams streams = new KafkaStreams(builder, config);  
streams.start();
```

”

#3: True event-at-a-time stream processing; no microbatching



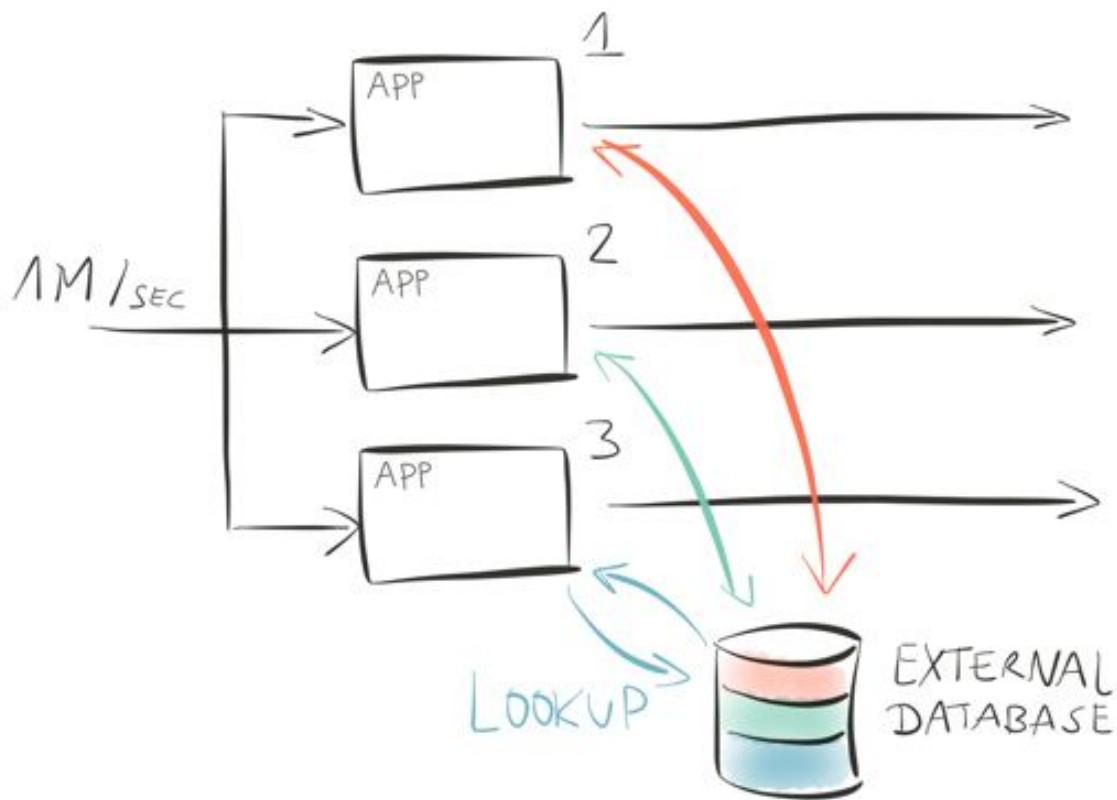
11

#4: Dataflow-style windowing based on event-time; handles late-arriving data

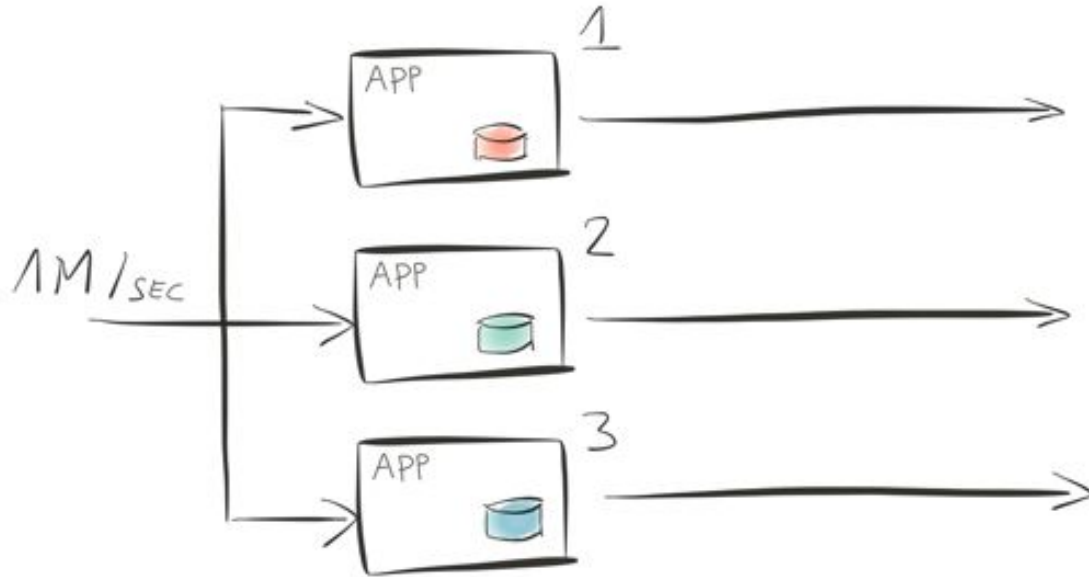
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#5: out-of-the-box support for *local state*; supports fast stateful processing

# EXTERNAL STATE

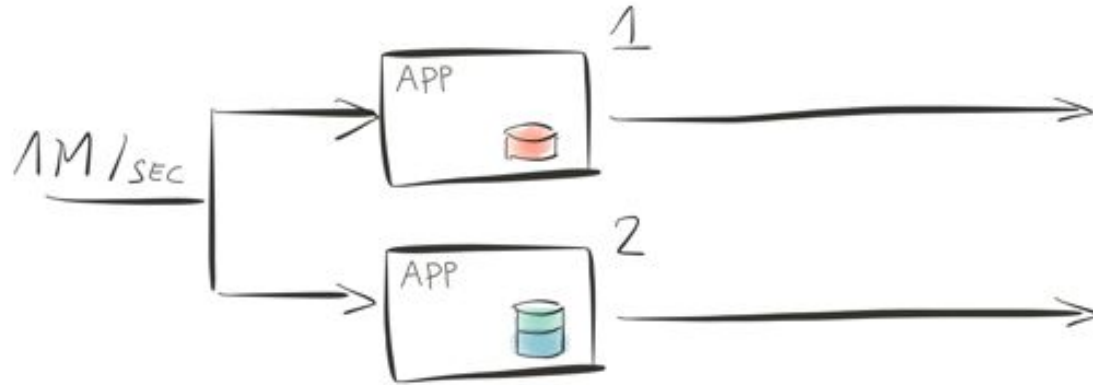


# LOCAL STATE





# FAULT-TOLERANT LOCAL STATE



”

#6: Kafka's Streams API allows reprocessing; useful to upgrade apps or do A/B testing

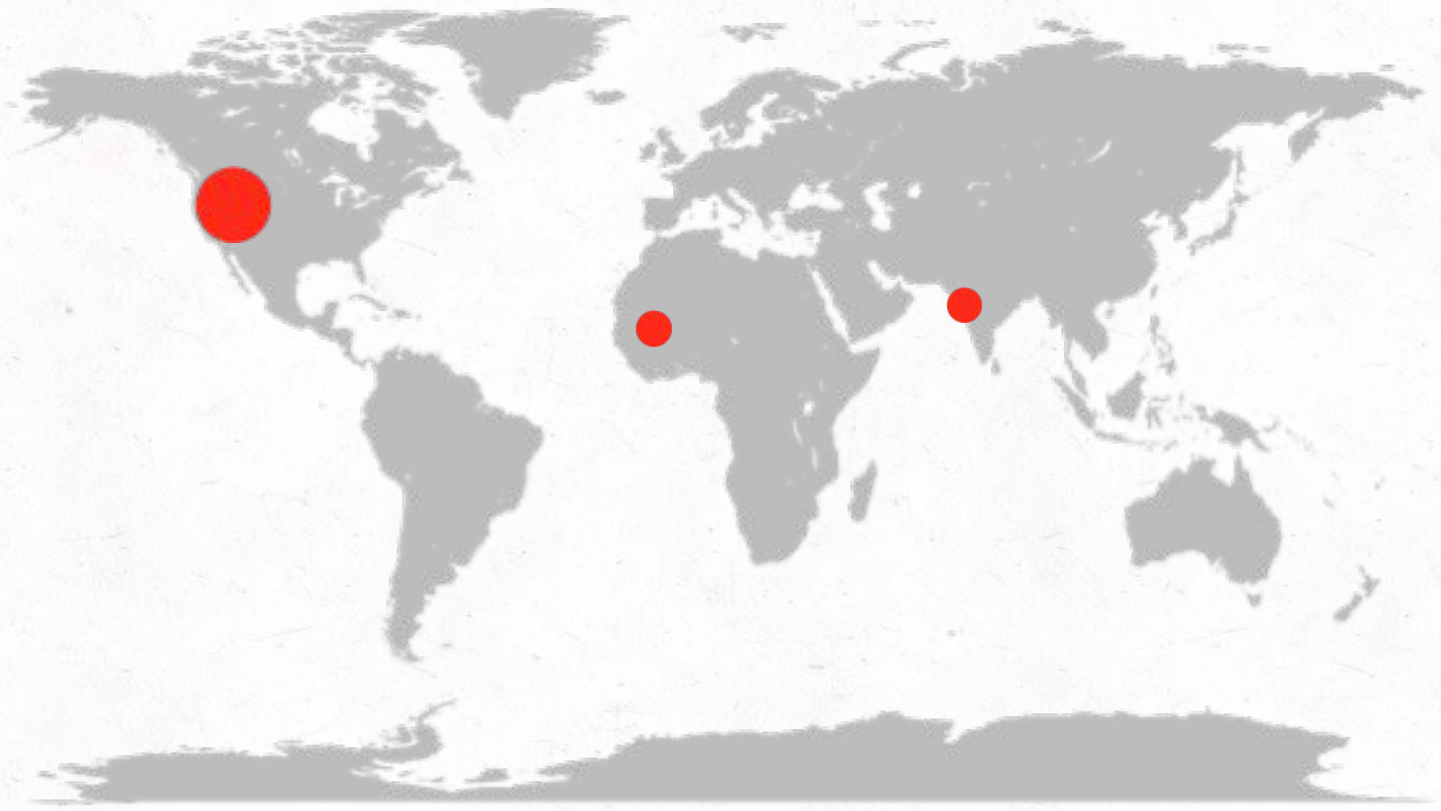
# REPROCESSING



0	1	2	3	4	5	6	7	8
---	---	---	---	---	---	---	---	---



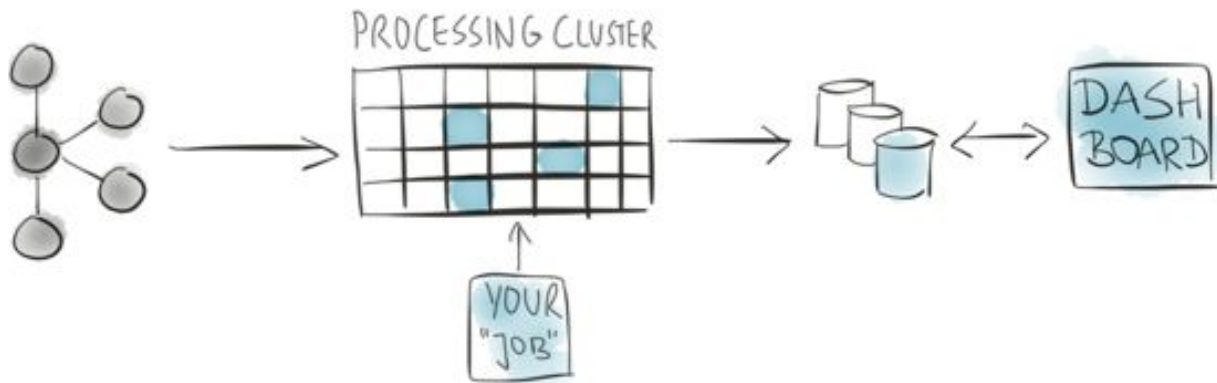
# REAL-TIME DASHBOARD FOR SECURITY MONITORING





# KAFKA'S STREAMS API: SIMPLE IS BEAUTIFUL

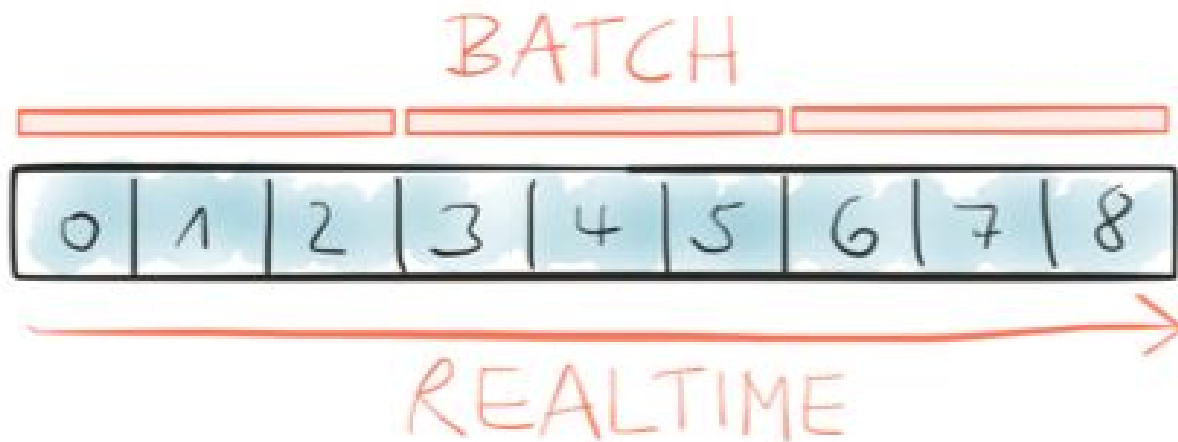
Vision 1



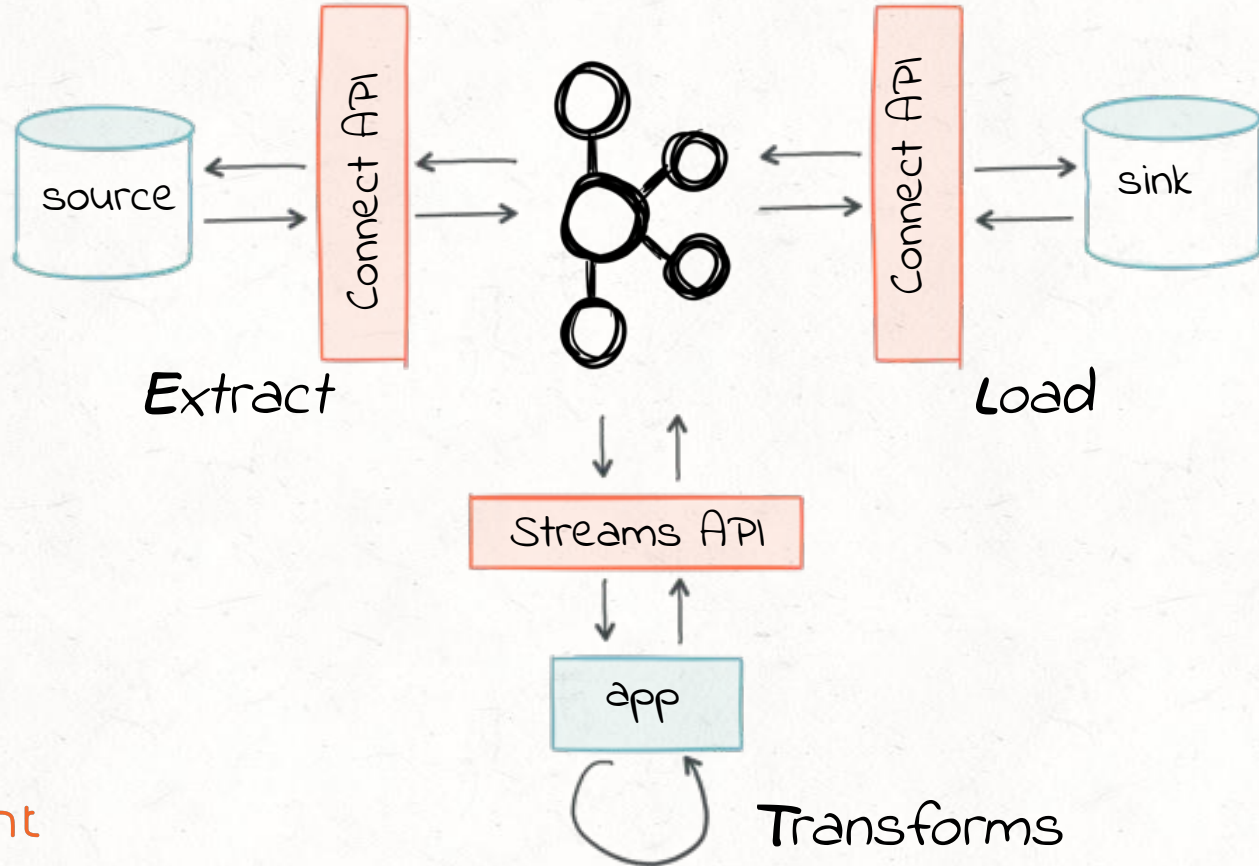
Vision 2

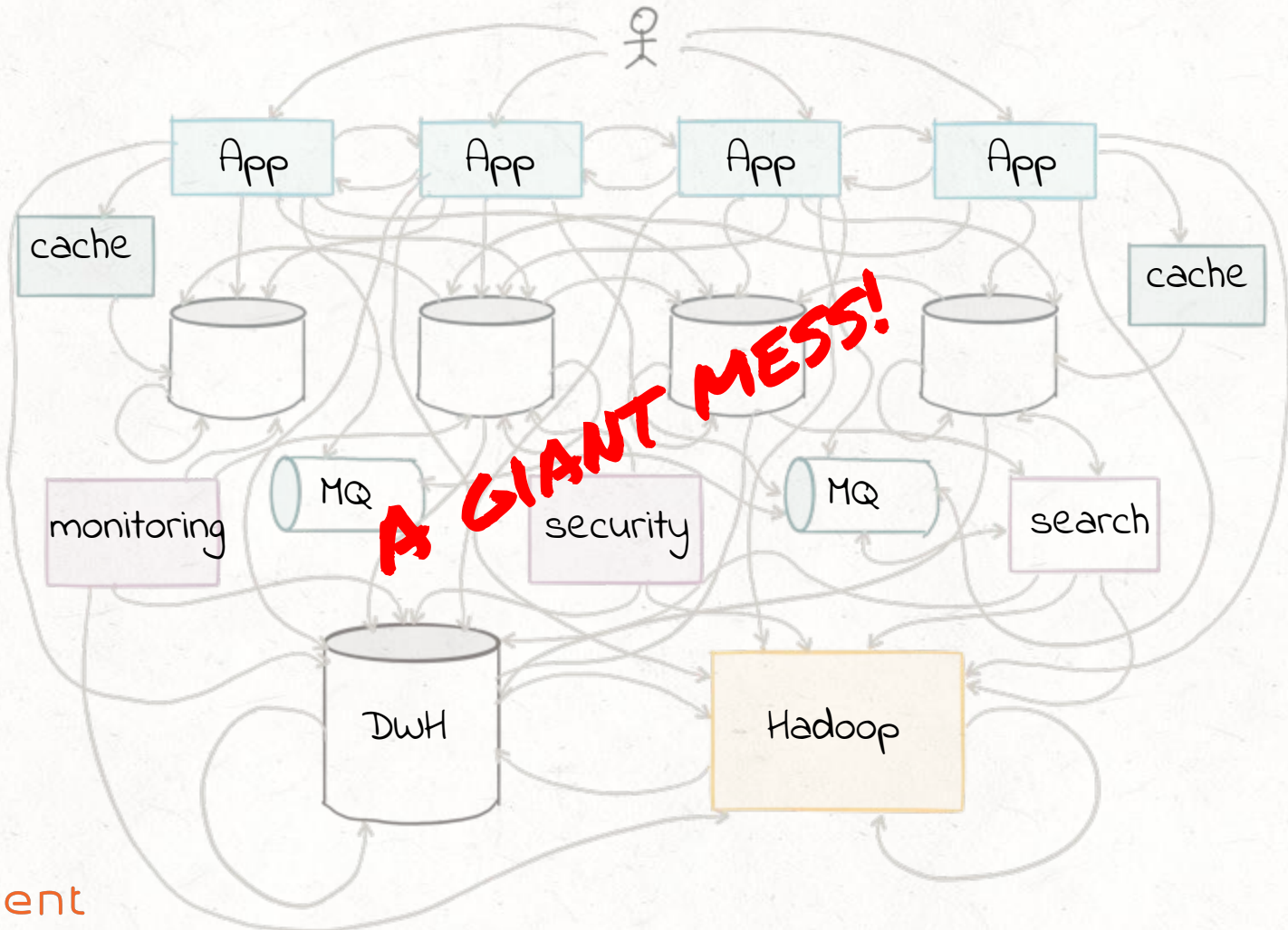


# LOGS UNIFY BATCH AND STREAM PROCESSING



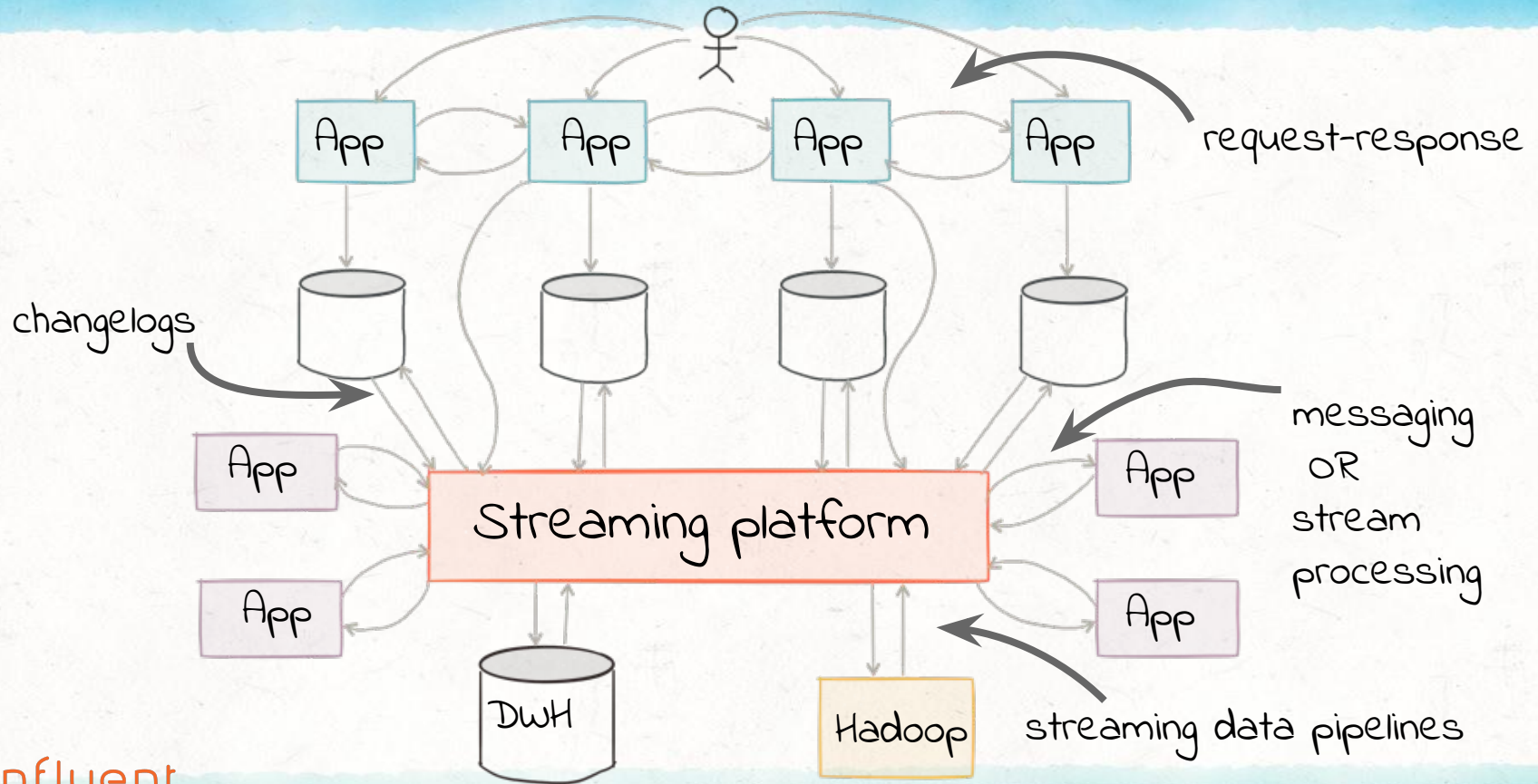
# NEW SHINY FUTURE OF ETL: KAFKA







# ALL YOUR DATA ... EVERYWHERE ... NOW



# VISION: ALL YOUR DATA ... EVERYWHERE ... NOW



THANK YOU!

@nehanarkhede