DATA+AI SUMMIT 2022

Backfill Streaming Data Pipelines in Kappa Architecture

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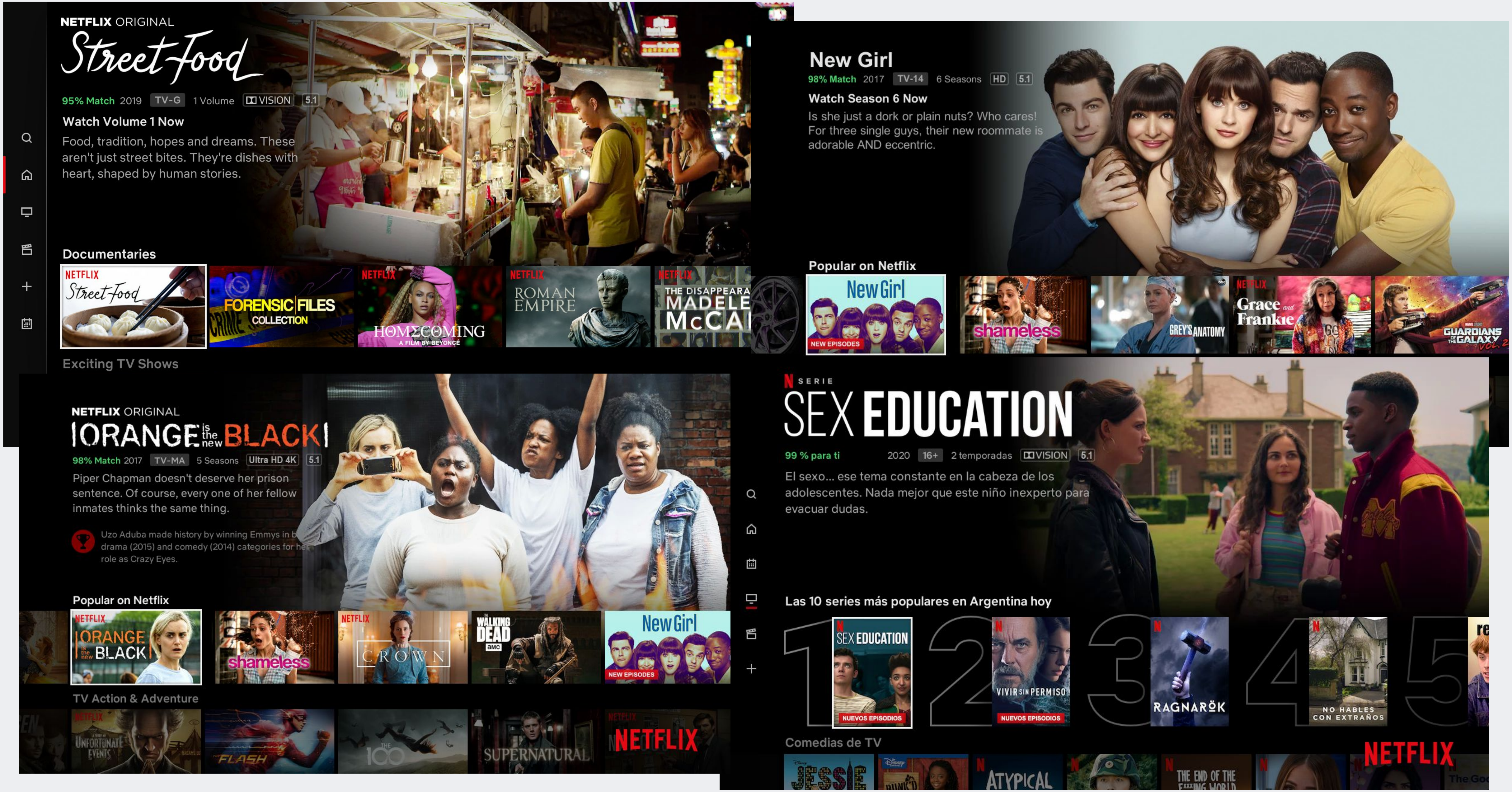
ORGANIZED BY databricks

Agenda

- ❖ Why backfill streaming pipelines
- ❖ Existing approaches
- ❖ Backfill in Kappa Style using Data Lake
- ❖ Event ordering challenges
- ❖ Adopting Kappa backfill



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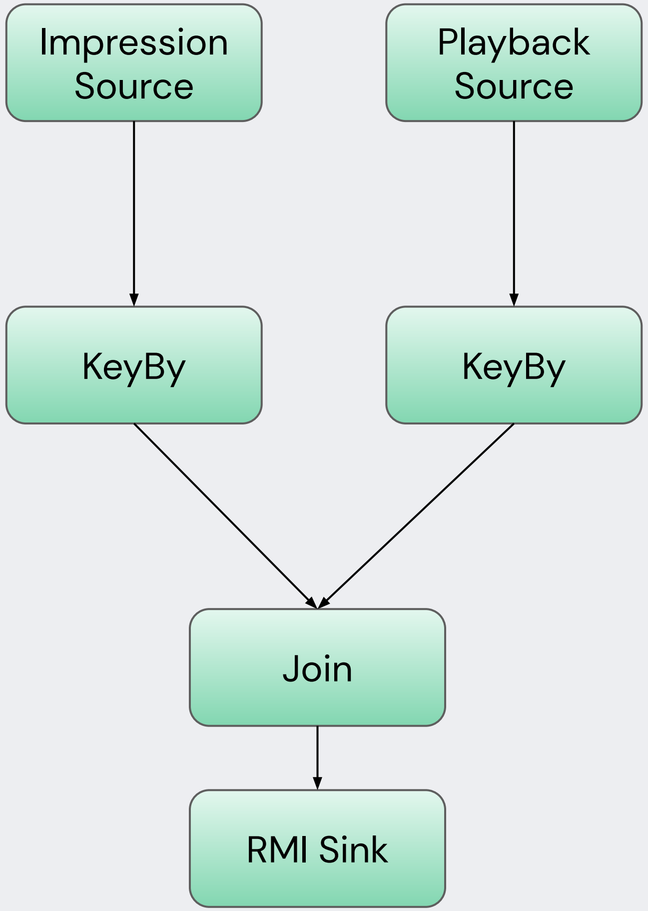
Event streaming at Netflix

Personalization DE built various data systems that power data analytics and ML algorithms.

Real-time Merched Impression (RMI) Flink App:

- Join Impression events with Playback events in real-time to attribute plays to impressions.
- Use Cases: Algo training, AB test analysis, etc.
- One of the largest stateful Flink apps at Netflix.

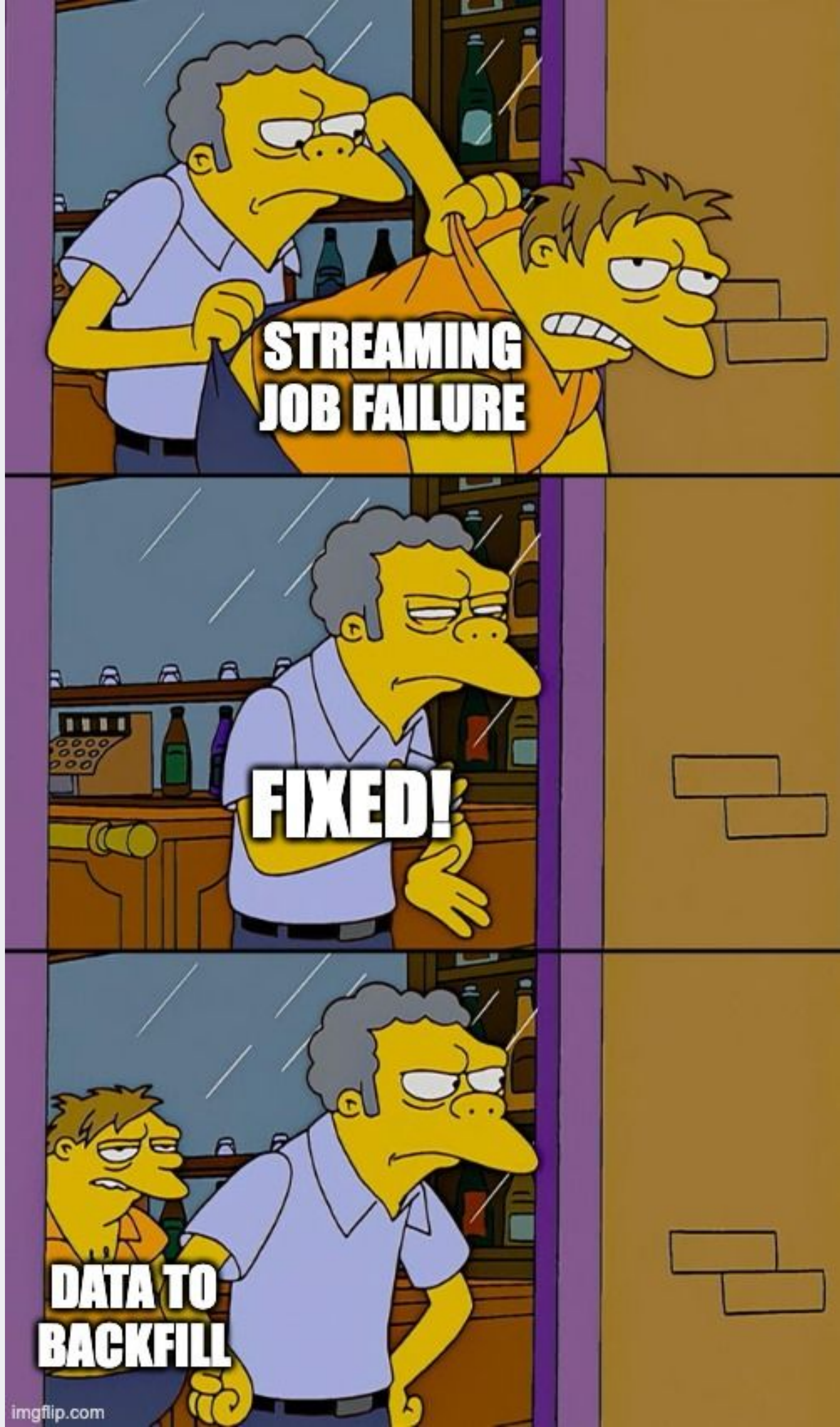


Event streaming operations

Streaming apps can fail due to various reasons:

- Source / sink failures
- Dependent service failures
- Upstream data changes

After failures, we need to backfill to mitigate downstream impact.



Event streaming operations

Possible types of backfilling needs:

- Correcting wrong data
- Backfilling missing data
- Bootstrapping state

How should we backfill?

Option #1: Replaying source events

The easiest way to backfill is by re-running the streaming job to reprocess source events from the problematic period.

Challenges

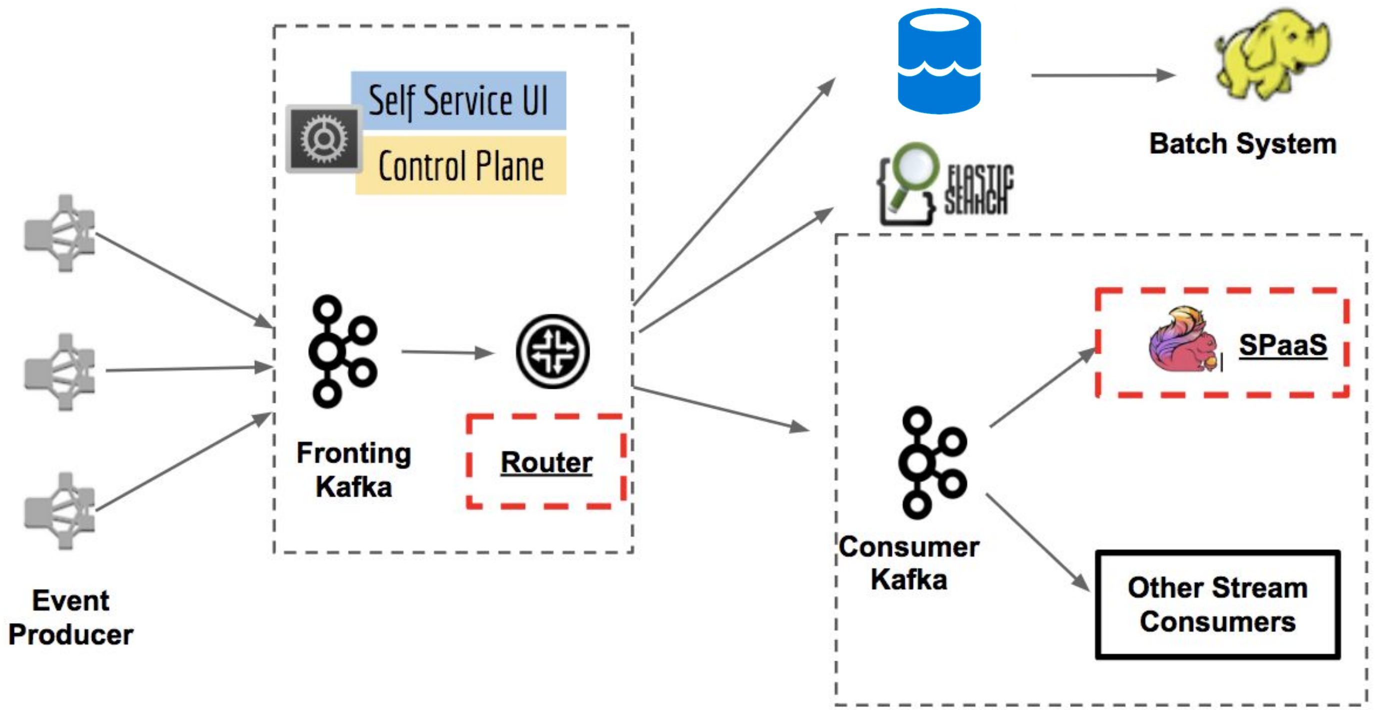
😭 Troubleshooting can take hours or days and source data can expire.

😭 Increasing message queue retention is very expensive.

- Row-based formats (e.g. Avro) have lower compression rate (v.s. Parquet/ORC).
- Low-latency storage solutions (e.g. EBS gp2) are more costly (v.s. S3).
- It would cost Netflix $93M/year to retain 30 days of data generated by all apps.

🤔 *Can we store events somewhere else?*

Netflix's Keystone[1] platform provides a routing service that makes Kafka events available in other storage systems, e.g. a **data lake** for batch processing.



[1] https://netflixtechblog.com/keystone-real-time-stream-processing-platform-a3ee651812a

Why Data Lake?

What is a data lake? 🛢

A data lake[1] is a central location that stores a large amount of data in its native raw format, using a flat architecture and object storage.

- Frameworks: Delta Lake, Apache Iceberg (Netflix's choice)

Why data lake?

💖 **Cost effective**: data are stored in compressed formats e.g. Parquet.
💖 Other features: file pruning, schema evolution, engine-agnostic, etc.

[1] https://databricks.com/discover/data-lakes/introduction

Kafka events stored in an Iceberg table

Playback Kafka Events

```
{
        "account_id":98524989,
        "show_id":4236781,
        "view_duration_sec": 123,
        …
},
{
        "account_id":87934298,
        "show_title_id":8754782,
        "view_duration_sec": 45,
        …
},
{
        "account_id":79403754,
        "show_id":3648295,
        "view_duration_sec": 81,
        …
},
…
```

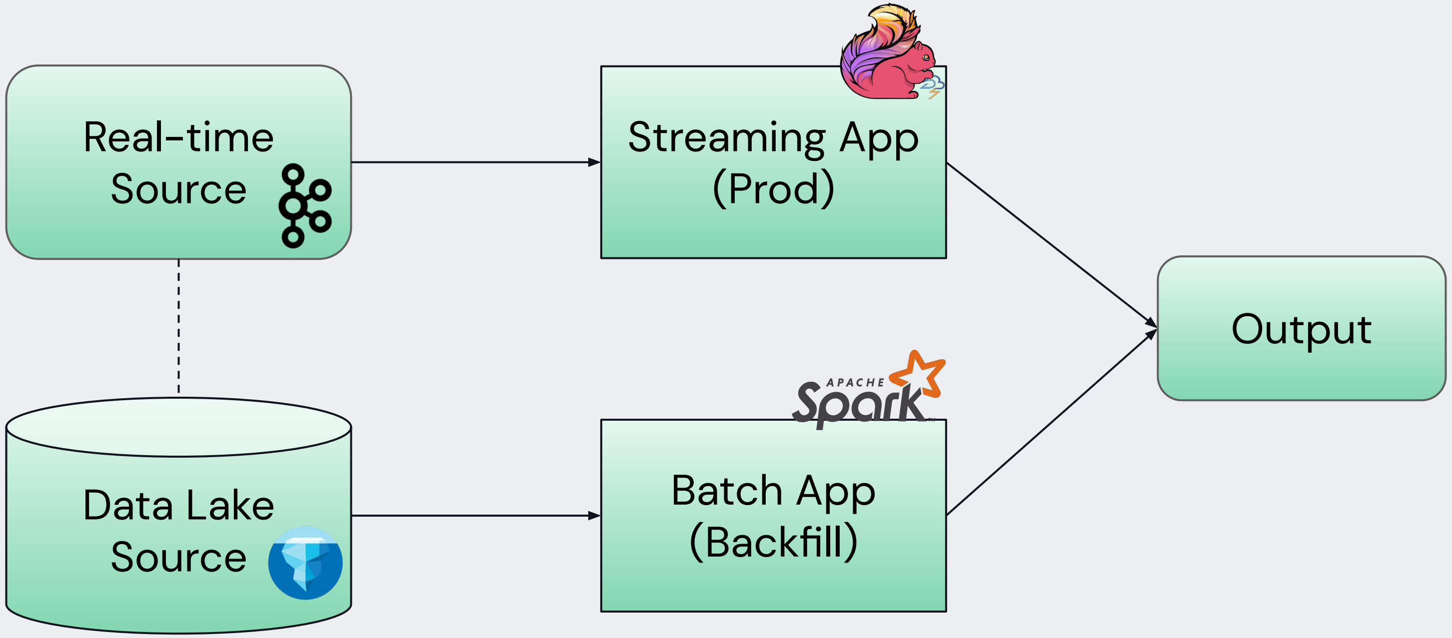
Playback Iceberg Table

account_id	show_id	view_duration	__metadata__
98524989	4236781	123	{kafka_ingestion_ts: …}
87934298	8754782	45	{kafka_ingestion_ts: …}
79403754	3648295	81	{kafka_ingestion_ts: …}
…	…	…	…

🤔 *Can we backfill from the data lake?*

Option #2: Lambda Architecture

Build and maintain a batch-based application (e.g. Spark job) that is equivalent to the streaming application but reads from Iceberg tables.



Option #2: Lambda Architecture

Build and maintain a batch-based application (e.g. Spark job) that is equivalent to the streaming application but reads from Iceberg tables.

Challenges

😵 Initial development of such batch job can take days or weeks, incl. data validation between two different applications.

😵 Continuous engineering efforts to keep the batch app up to date.

Option #3: Unified batch and streaming

Taking two birds with one stone?

Frameworks

- Apache Flink: offers both batch and streaming modes.
- Apache Beam[1]: a unified programming model for batch and streaming data processing pipelines.

Limitations

😭 Flink requires significant code changes to run batch mode.

😭 Beam only has partial support on state, timers, and watermark[2].

[1] https://beam.apache.org/about/ [2] https://beam.apache.org/documentation/runners/capability-matrix/

Backfill Option Comparison

Pros & cons in summary

Rerunning Streaming Job

- Method: Rerun the streaming app before source data expire.
- Pros: Backfill using the same app.
- Cons: Increasing message queue retention is expensive. 💸💸💸

Separate Batch Job

- Methodology: Maintain an equivalent batch app reading from a data lake.
- Pros: Low data retention cost in data lake.
- Cons: Engineers have to maintain two applications in parallel. 😰😰😰

Unified Batch & Streaming

- Prerequisite: Use a framework with both batch & streaming modes.
- Pros: Backfill using the batch mode.
- Cons: Might still require significant code changes. 💔💔💔

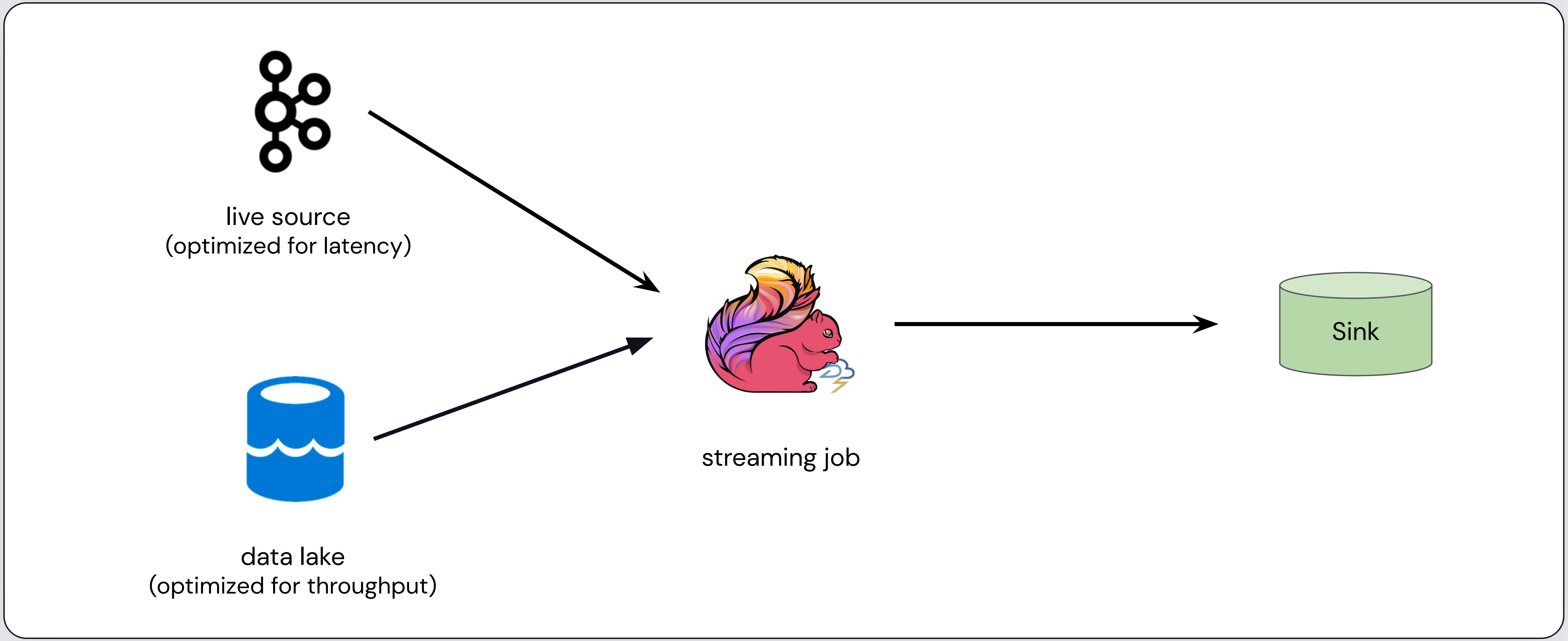
Can we combine the best things from all three worlds?

Backfilling
In Kappa Architecture
(feat. Data Lake)

Backfilling using Data Lake: Goals

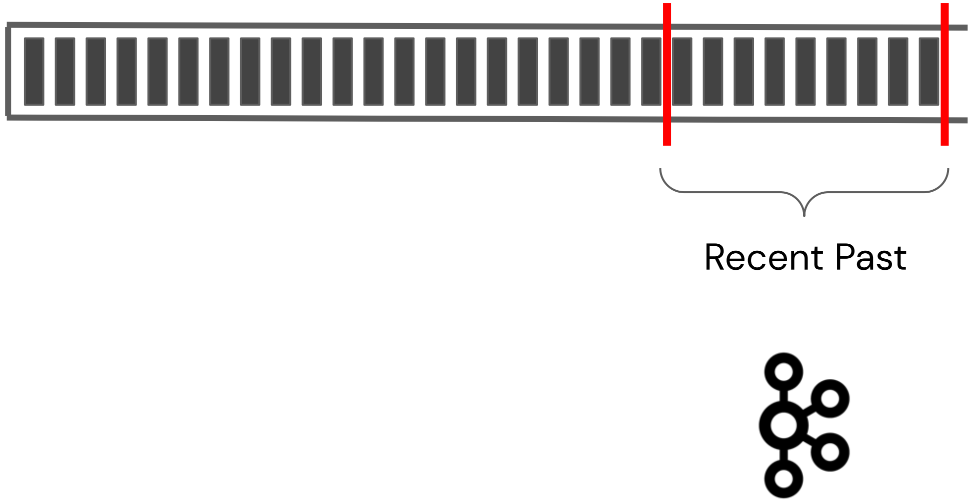
- Provide a generic solution that works for all classes of applications
- Minimal code changes to add support
- Scales horizontally to backfill quickly

Backfilling using Data Lake: Overview



Backfilling using Data Lake: Overview

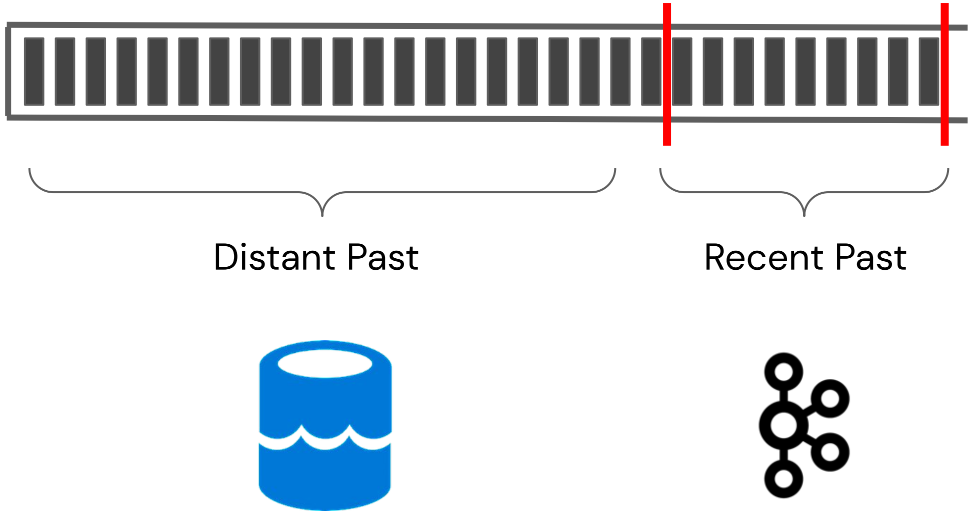
Semantics



Handling real-time data

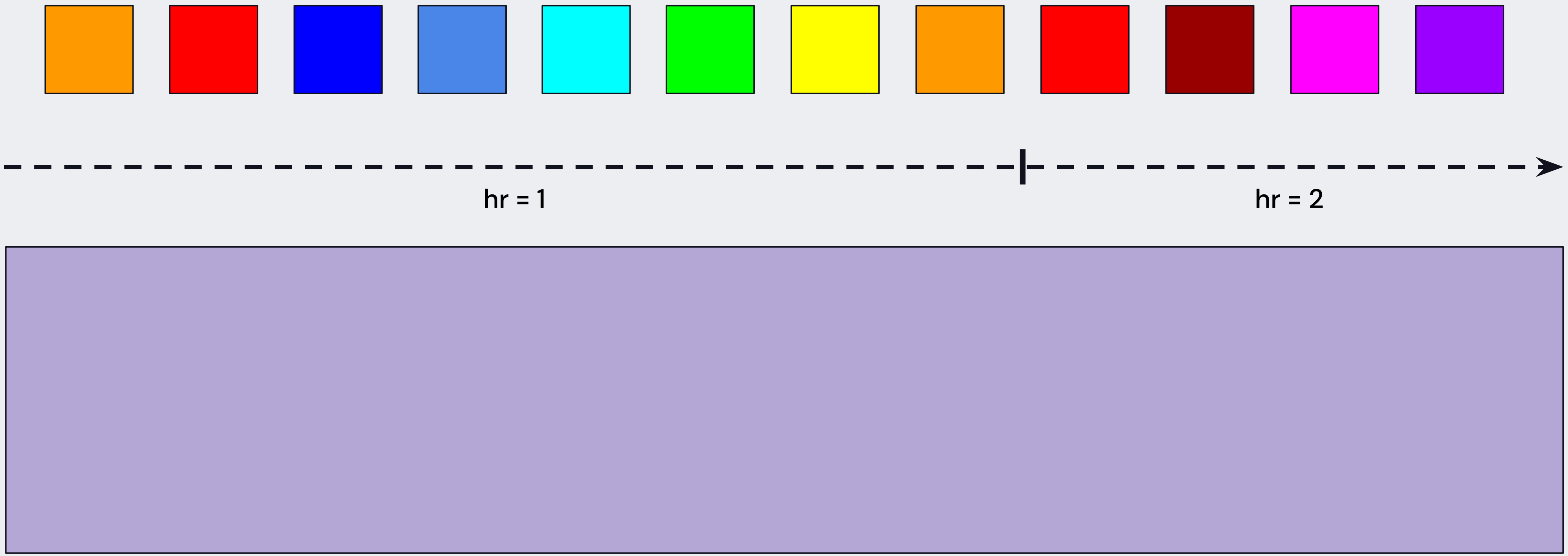
Backfilling using Data Lake: Overview

Semantics



Backfilling

Ingesting streaming data into data lake



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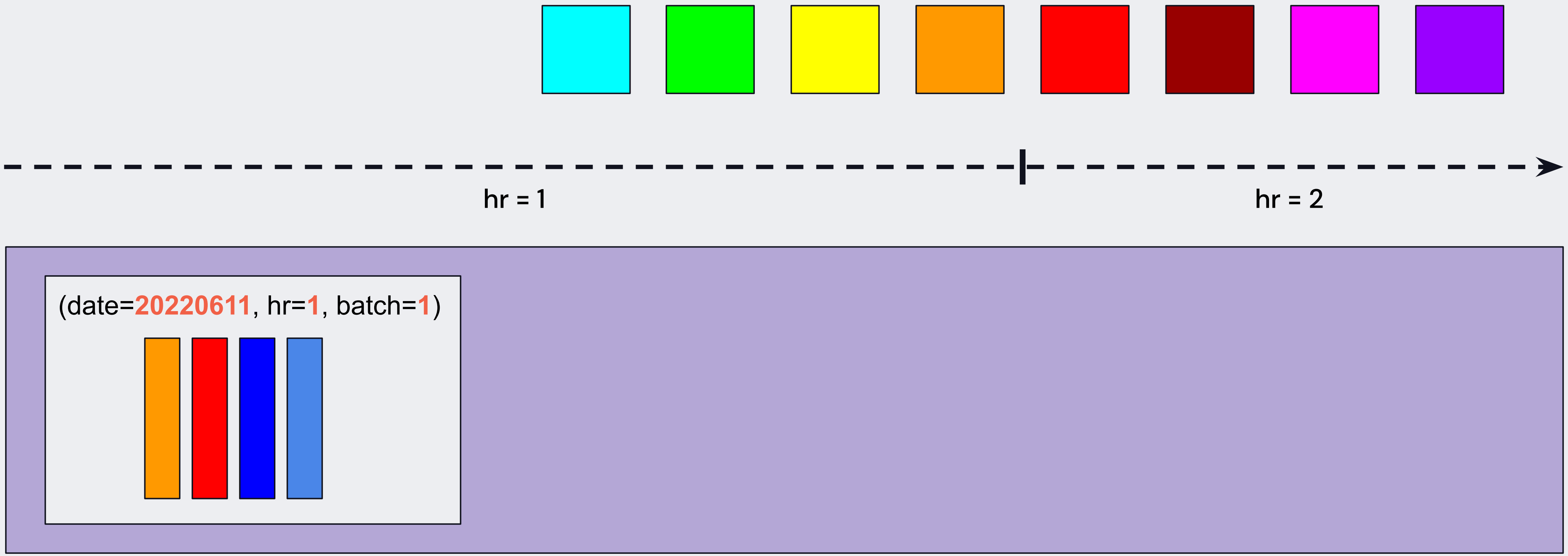

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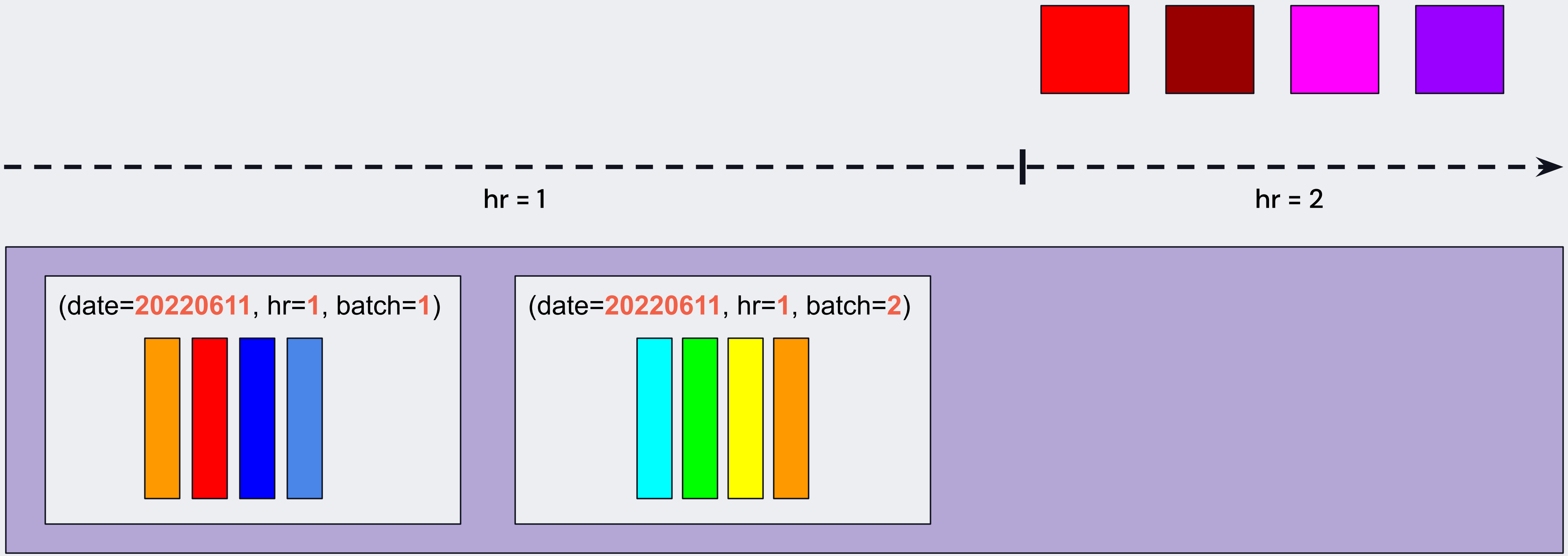

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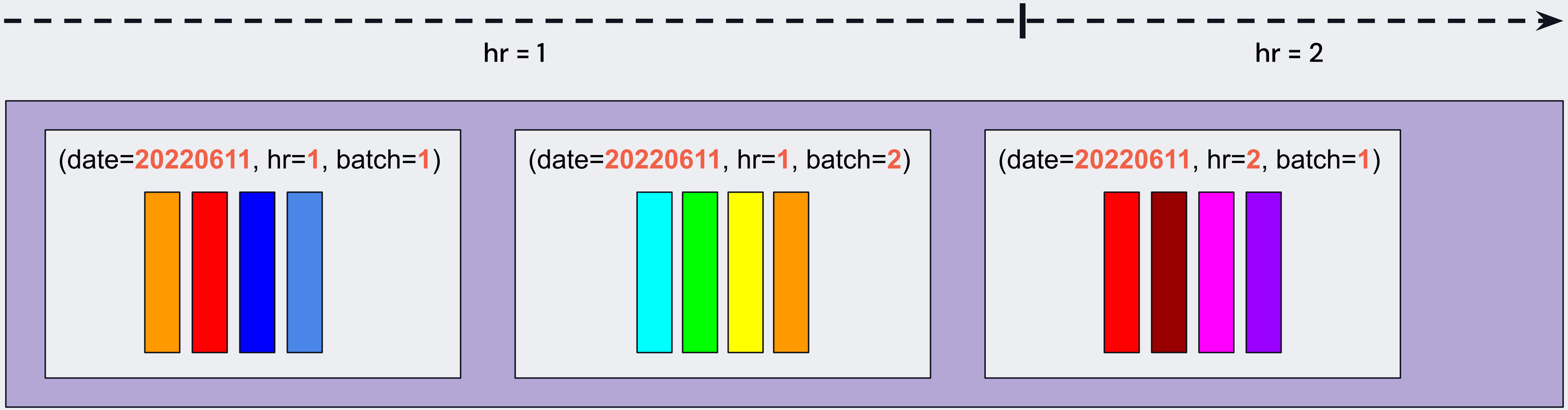
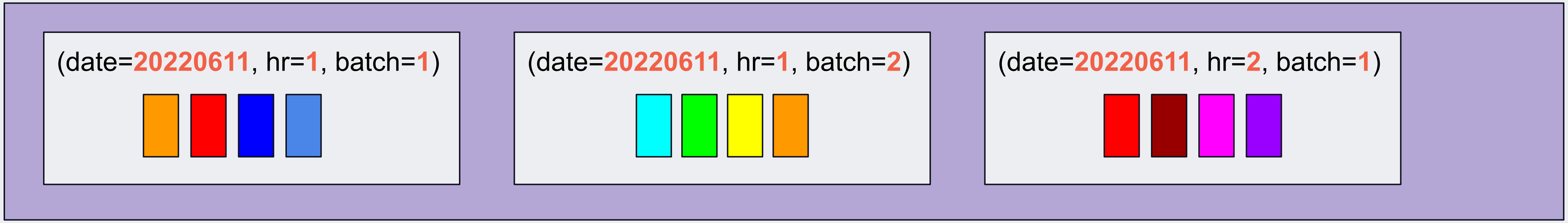


✔ Batching events results in good compression ratios.
✔ Avoids small file problem.

How to backfill?

- **Strawman 1:** Read events from files filtered by backfill dates

Strawman 1: Read events from selected files



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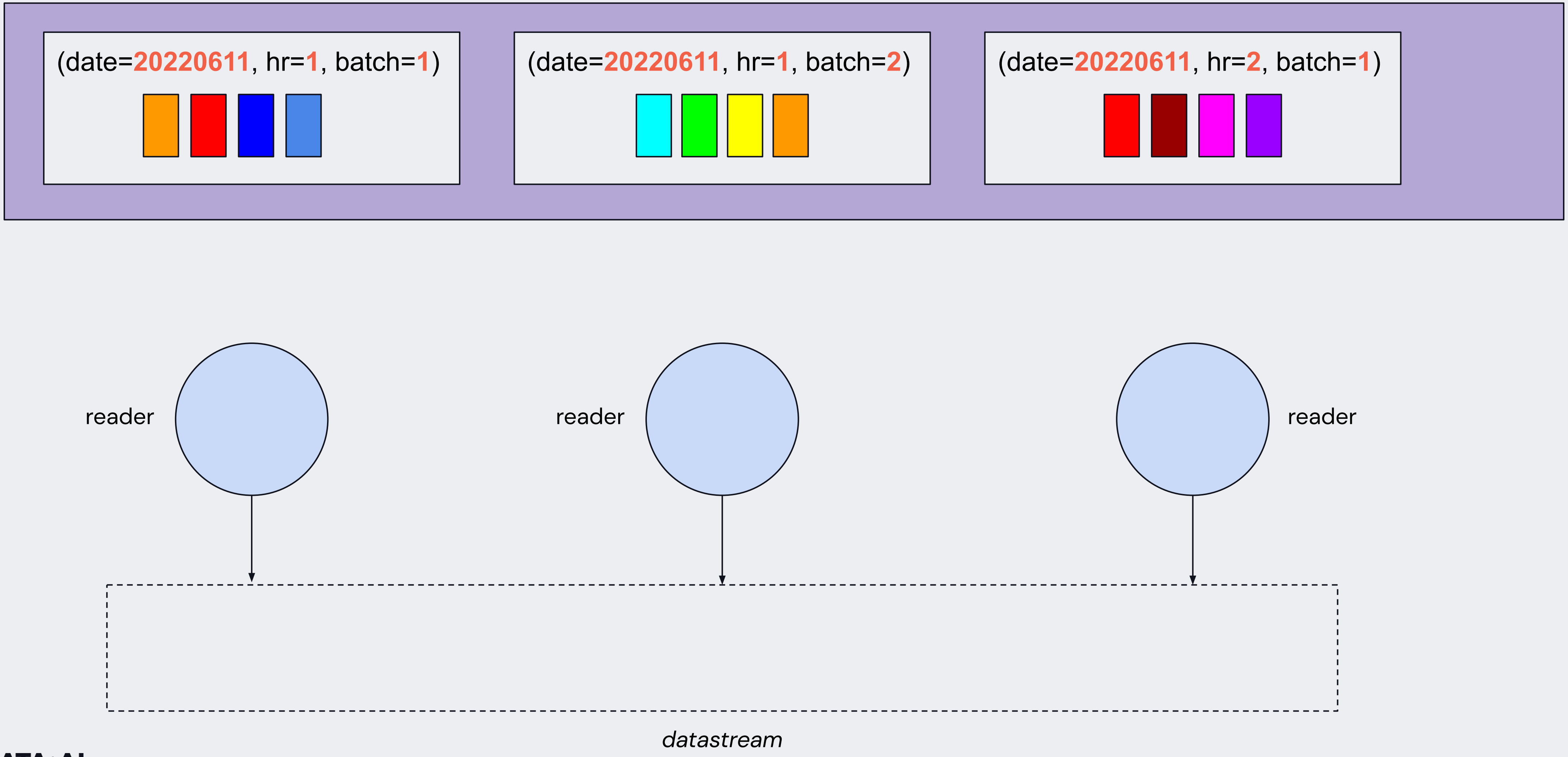

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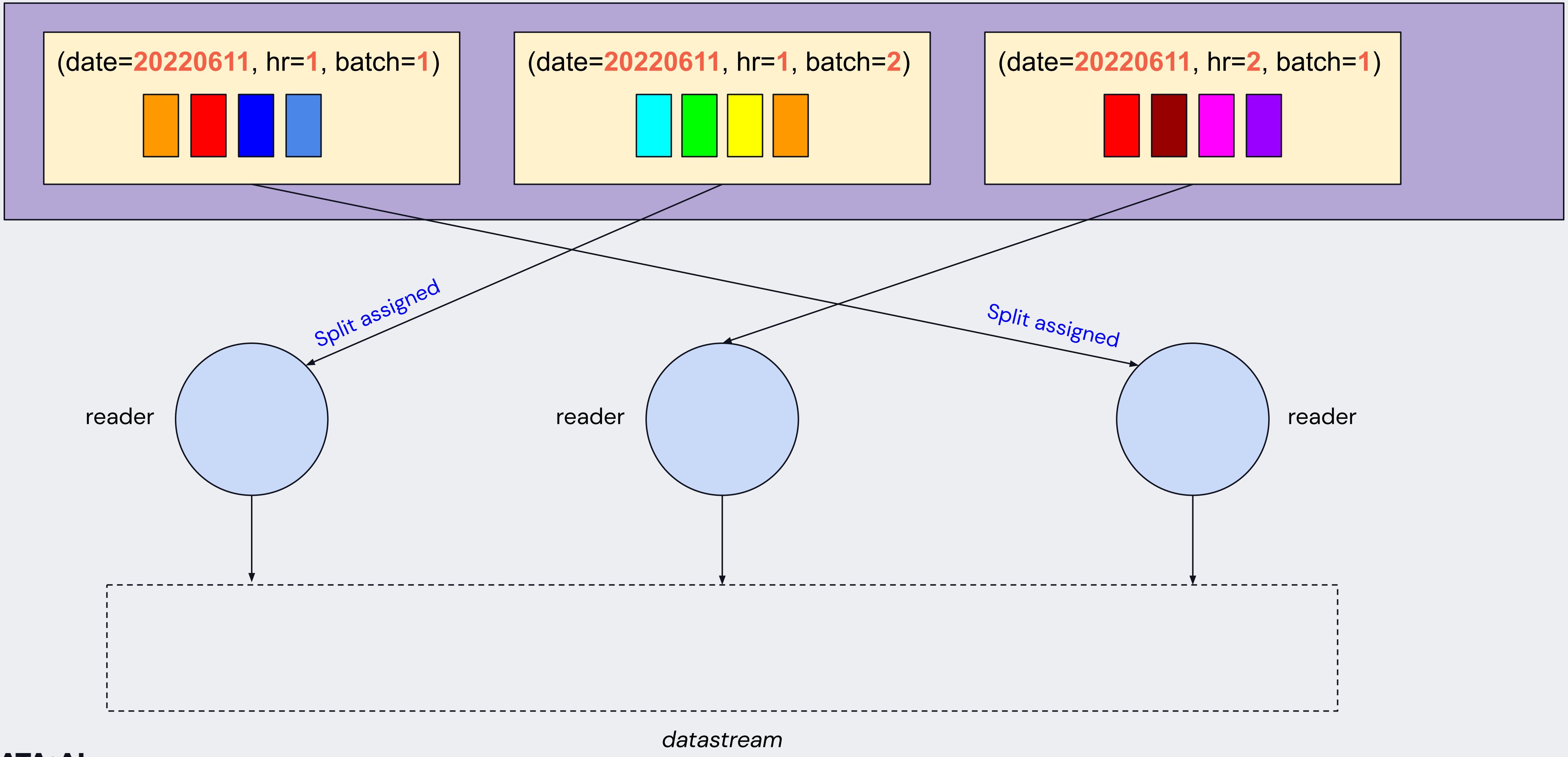

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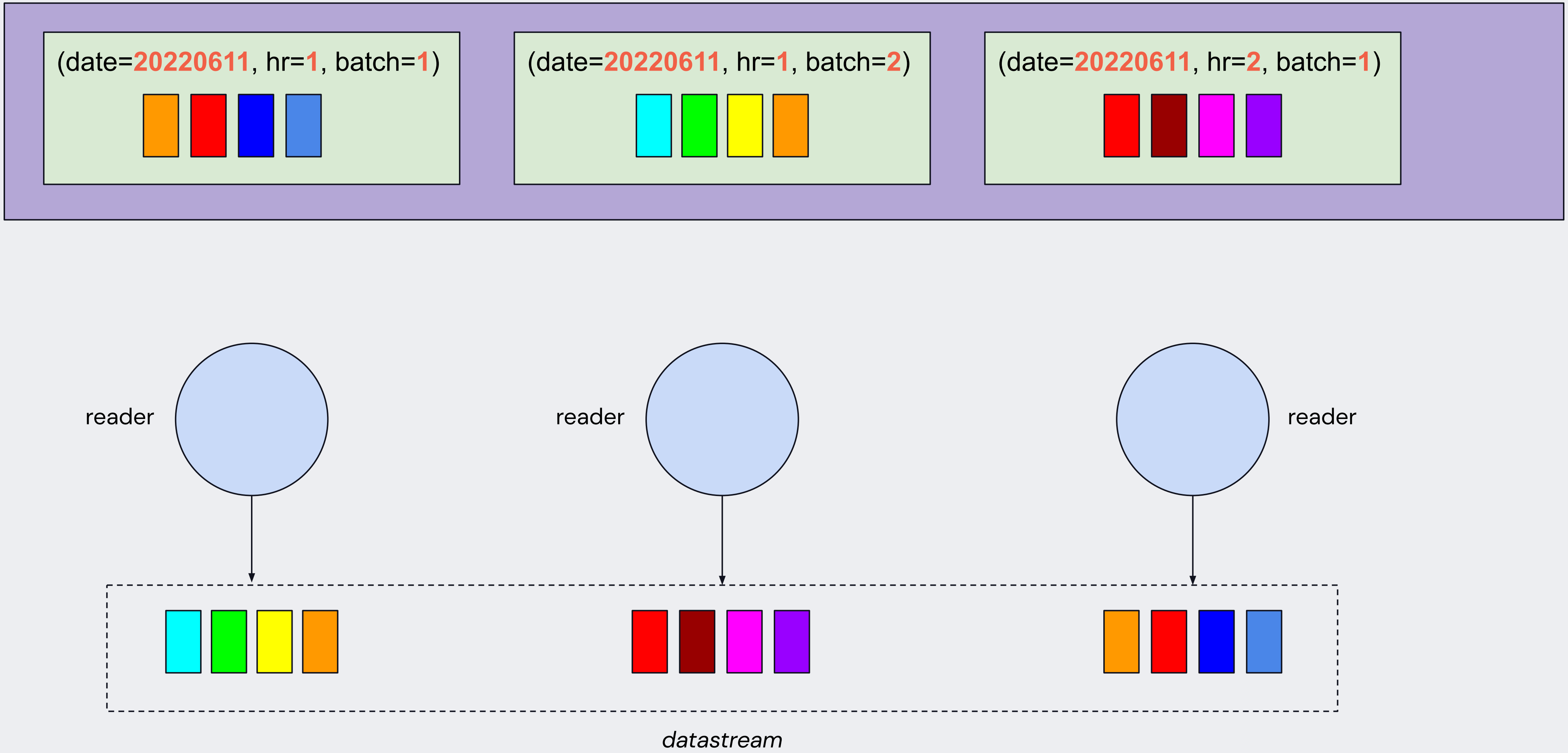
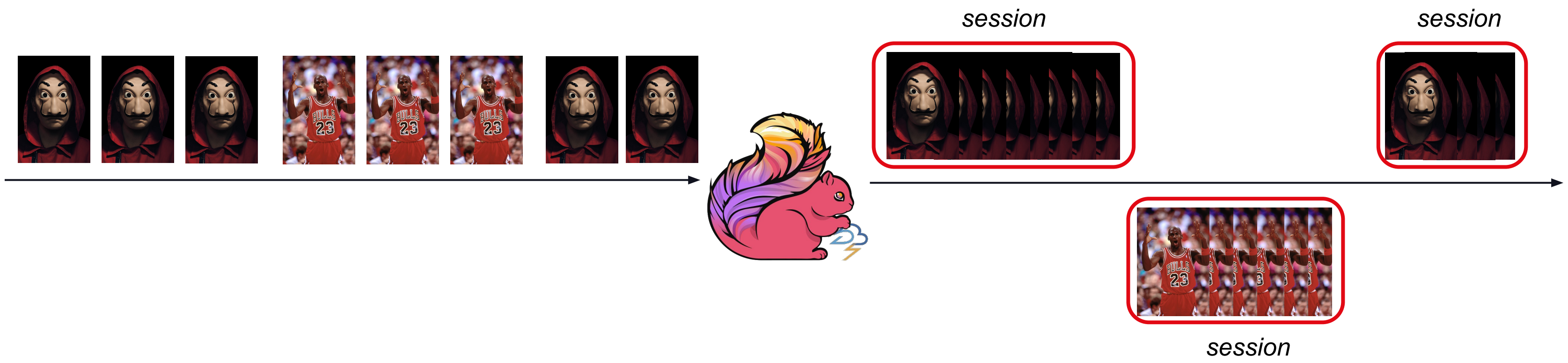


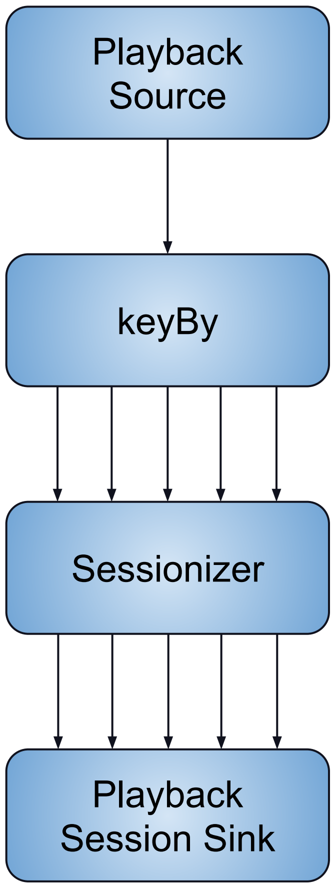
How to backfill?

- **Strawman 1:** Read events from files filtered by backfill dates
    - ✔ Scales horizontally to backfill quickly
    - ✖ Does not work for all types of applications

Challenge #1: Applications assume ordering

Example: Application that converts playback events into playback sessions





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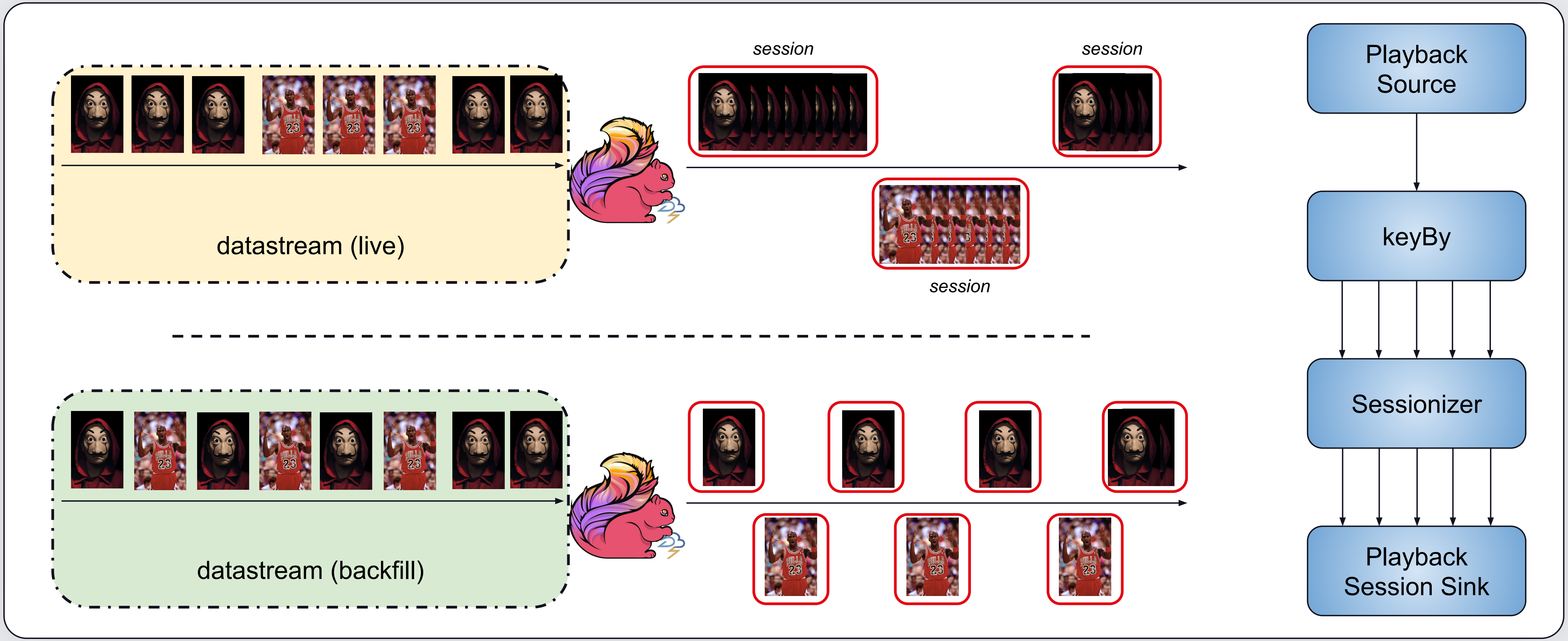

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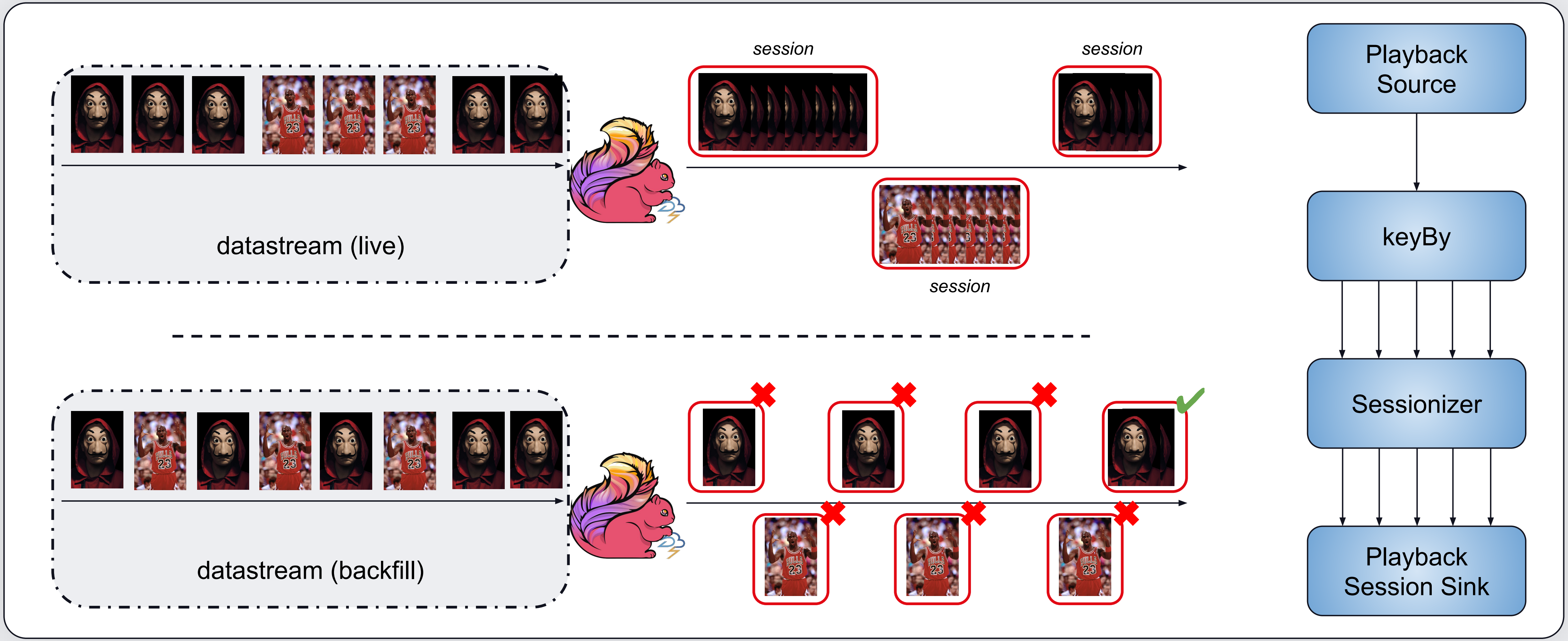
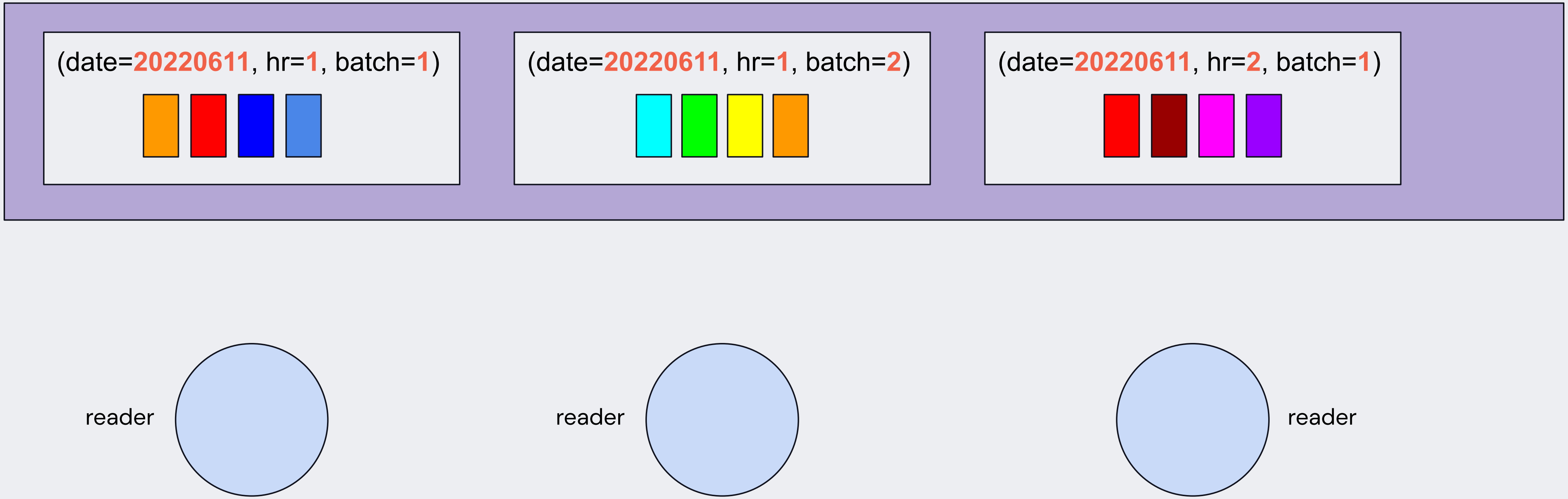


😭Different ordering leads to different results

Strawman 2: Order all files and read in order



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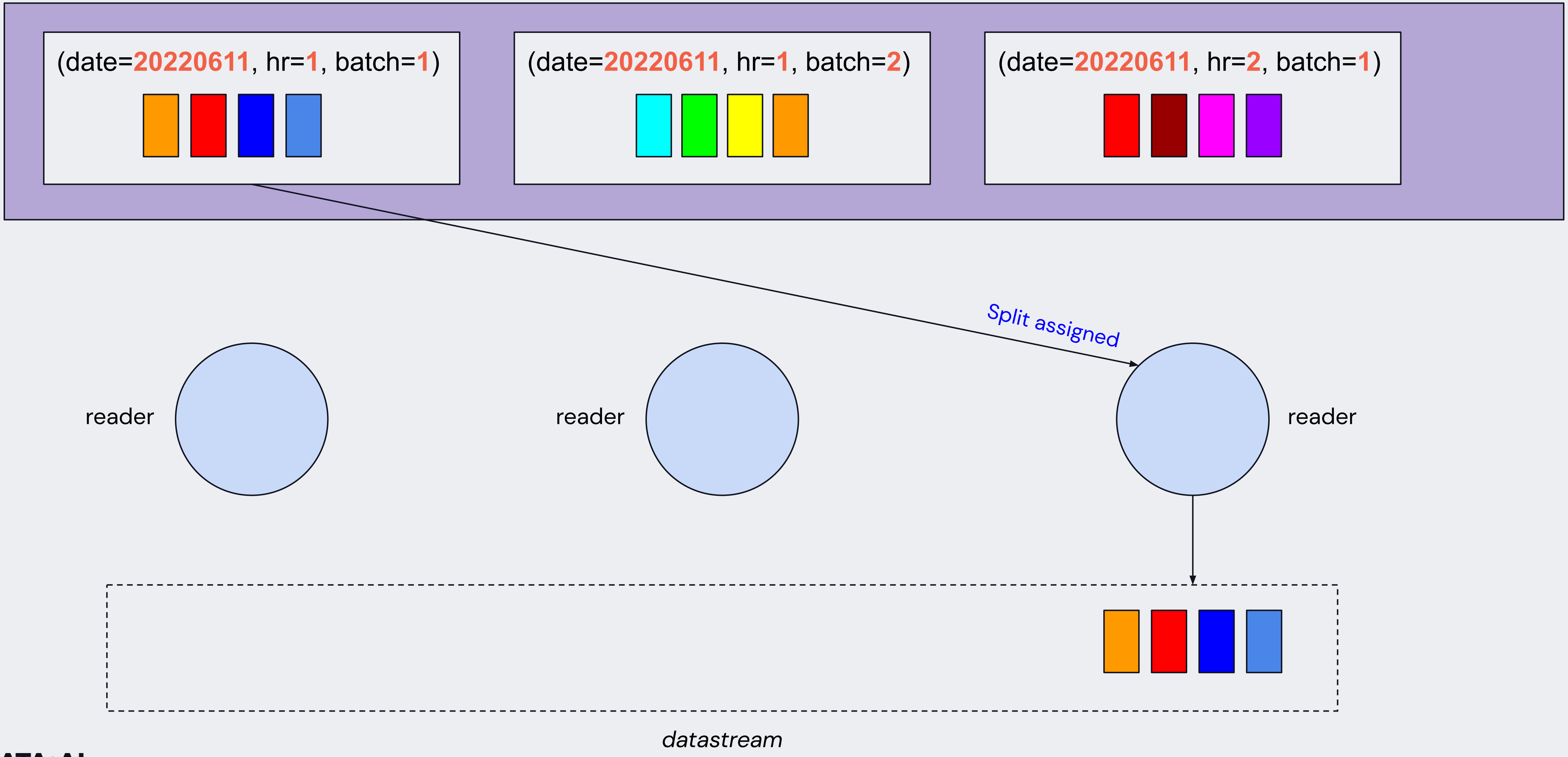

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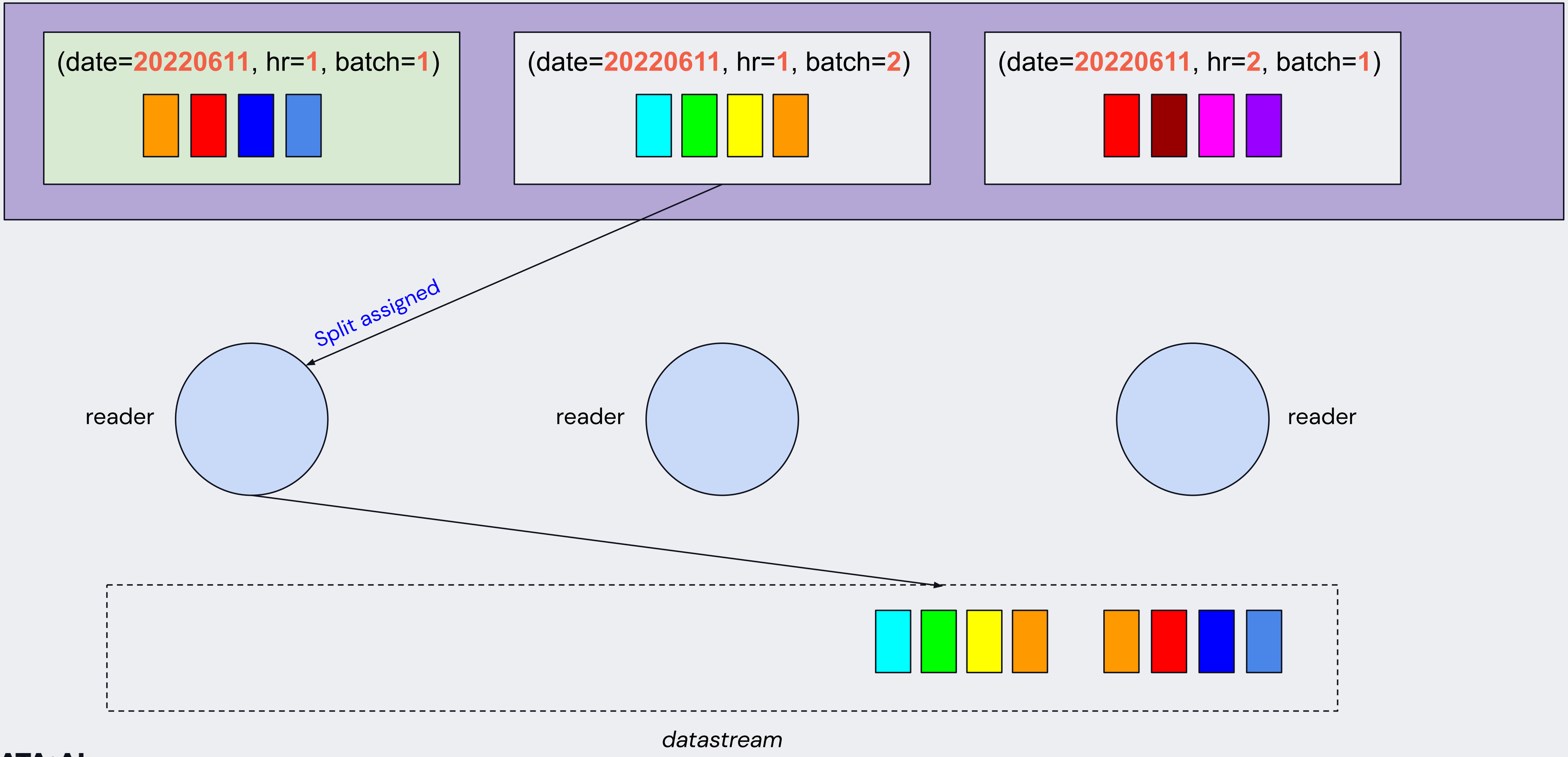

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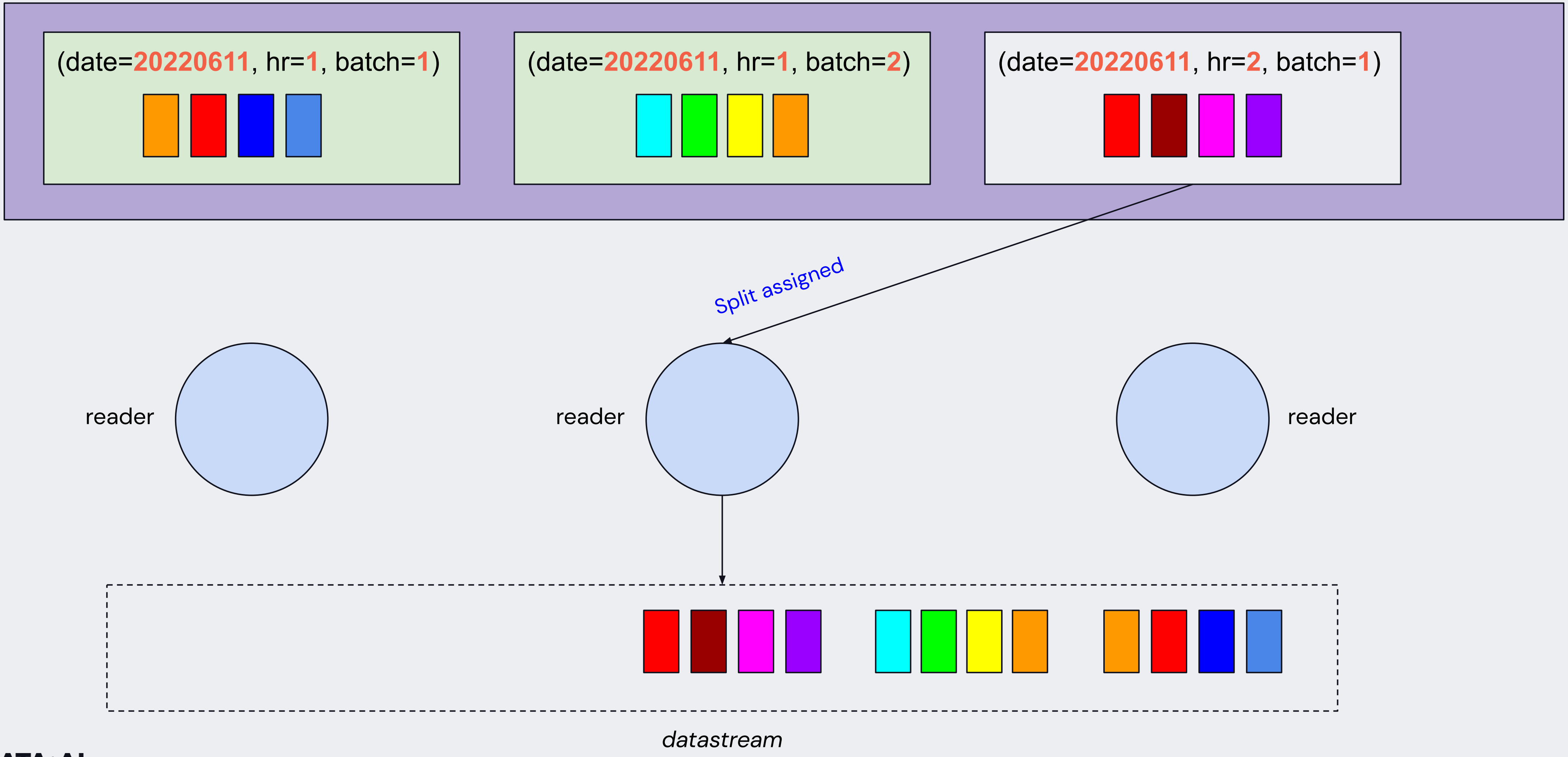


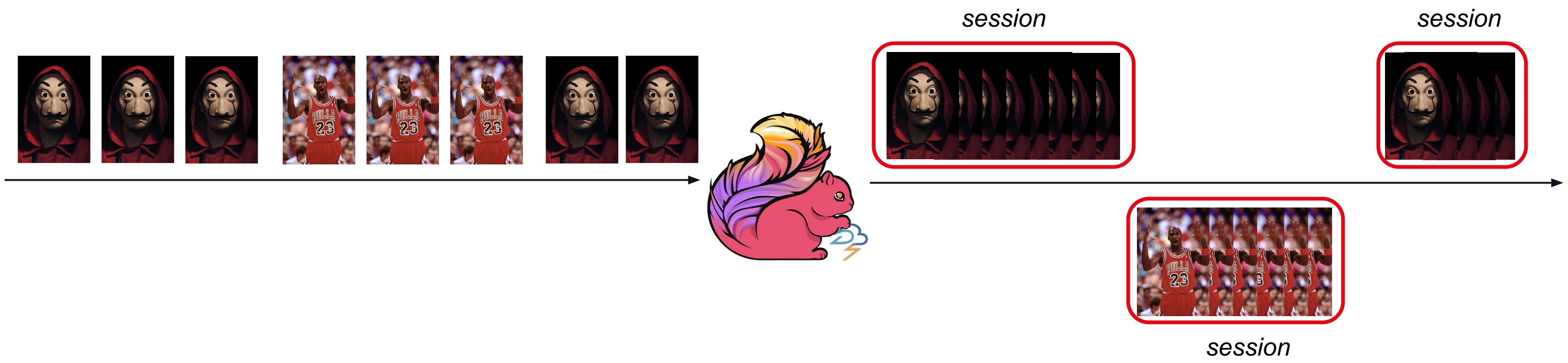
How to backfill?

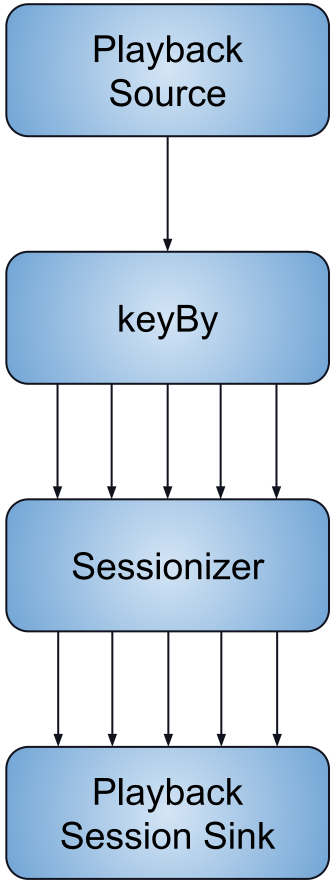
- **Strawman 1:** Read events from files filtered by backfill dates
  - ✔ Scales horizontally to backfill quickly
  - ✖ Does not work for all types of applications
- **Strawman 2:** Order all files and read them in order
  - ✔ Guarantees similar ordering semantics as the live traffic
  - ✖ Does not scale horizontally

But, not all streaming apps rely on strong ordering guarantees.

Event-Time Semantics

Example: Application that converts playback events into playback sessions





Event-Time Semantics

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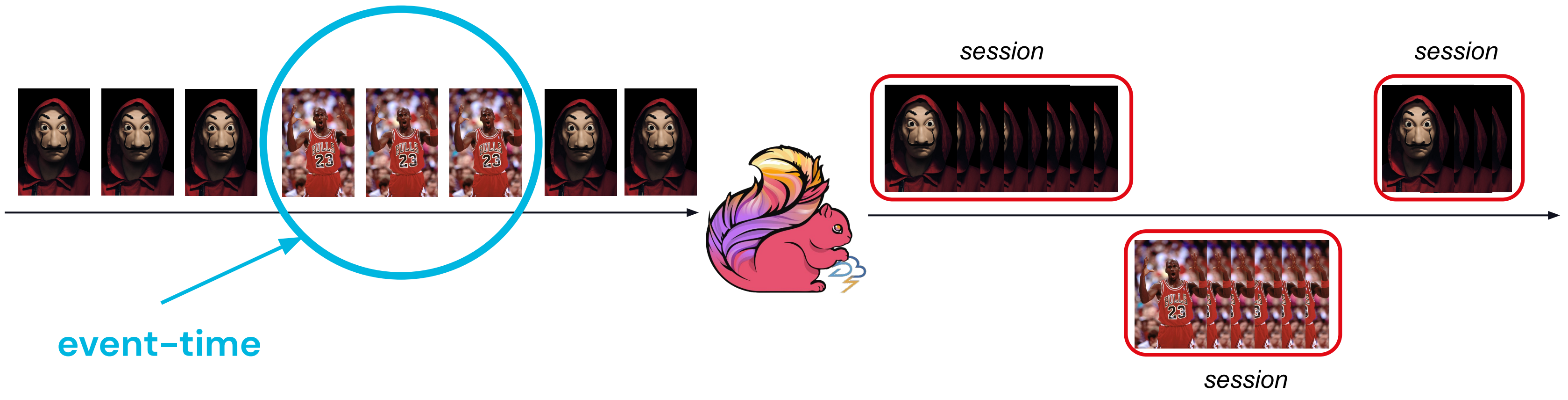
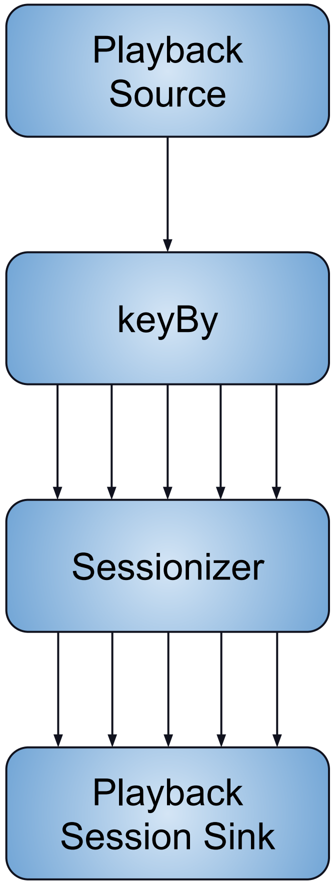
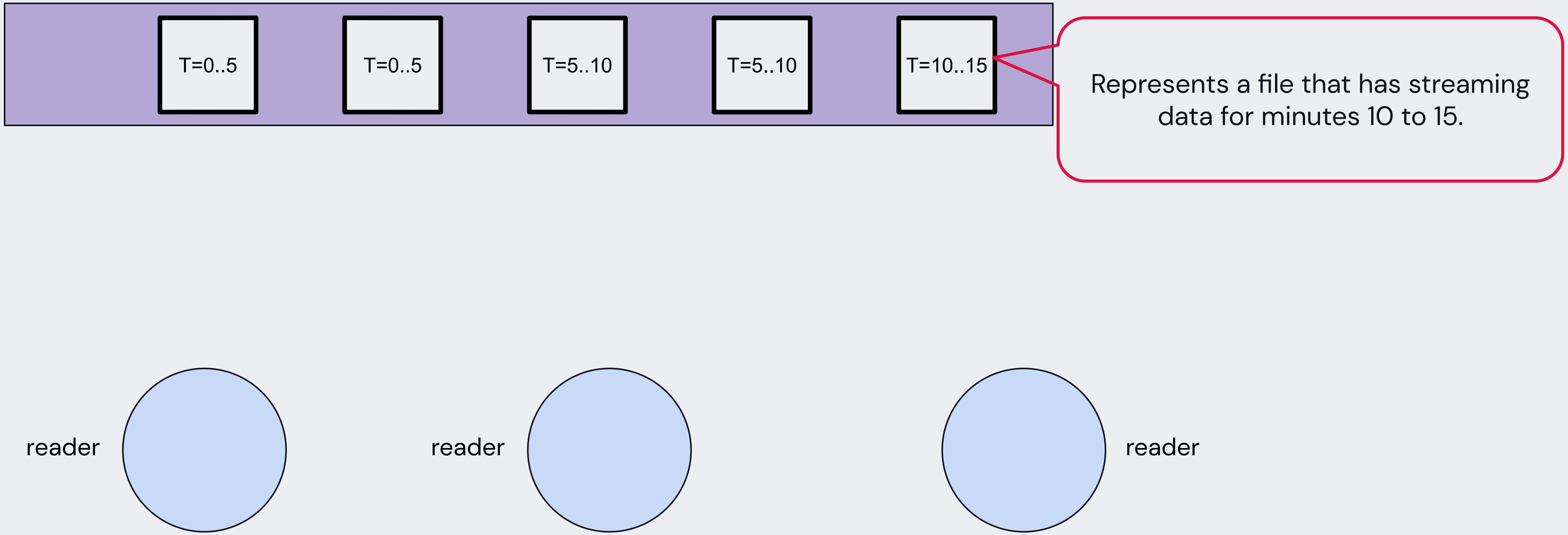




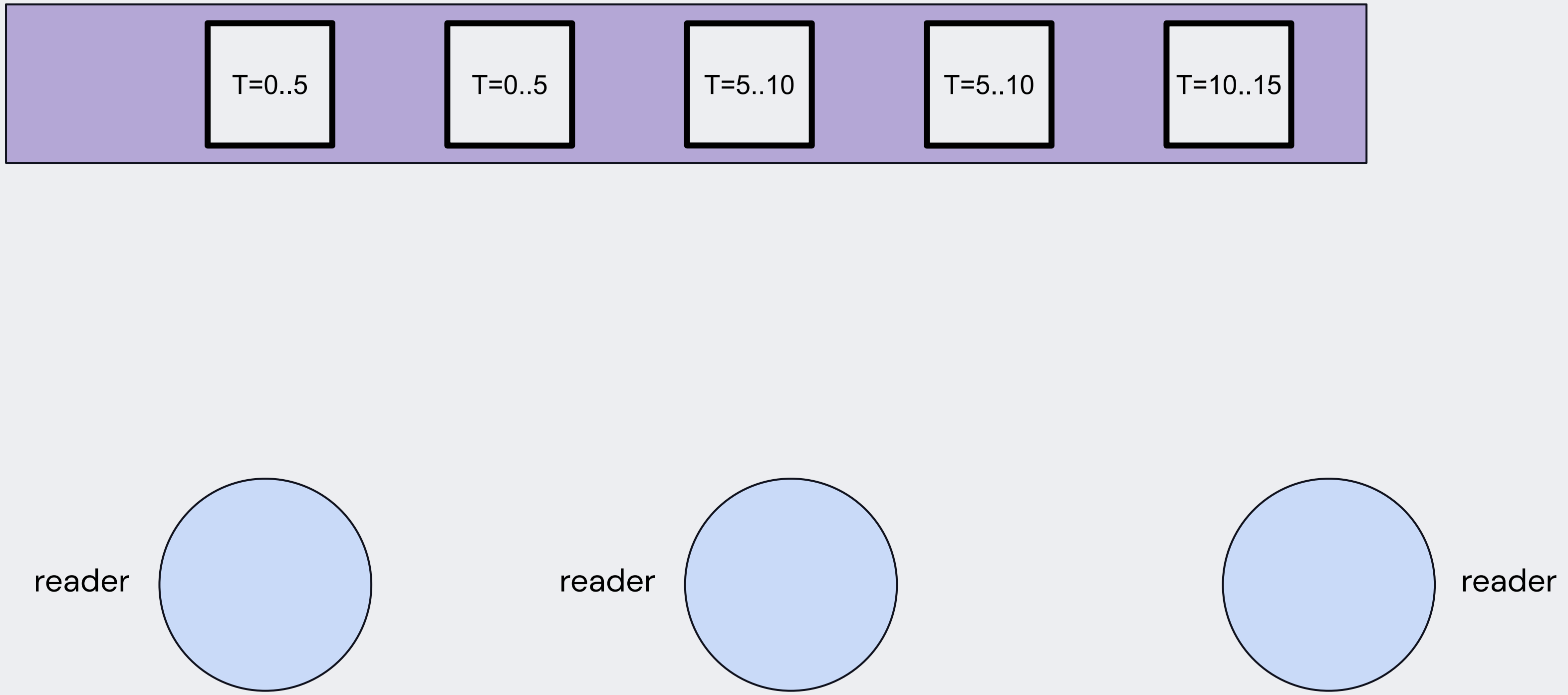
1. Sessions are derived from event timestamps - not ingestion times.
2. Because events can arrive late, applications tolerate lateness.

Idea: Use lateness tolerated by app

Solution: Use lateness tolerated by app

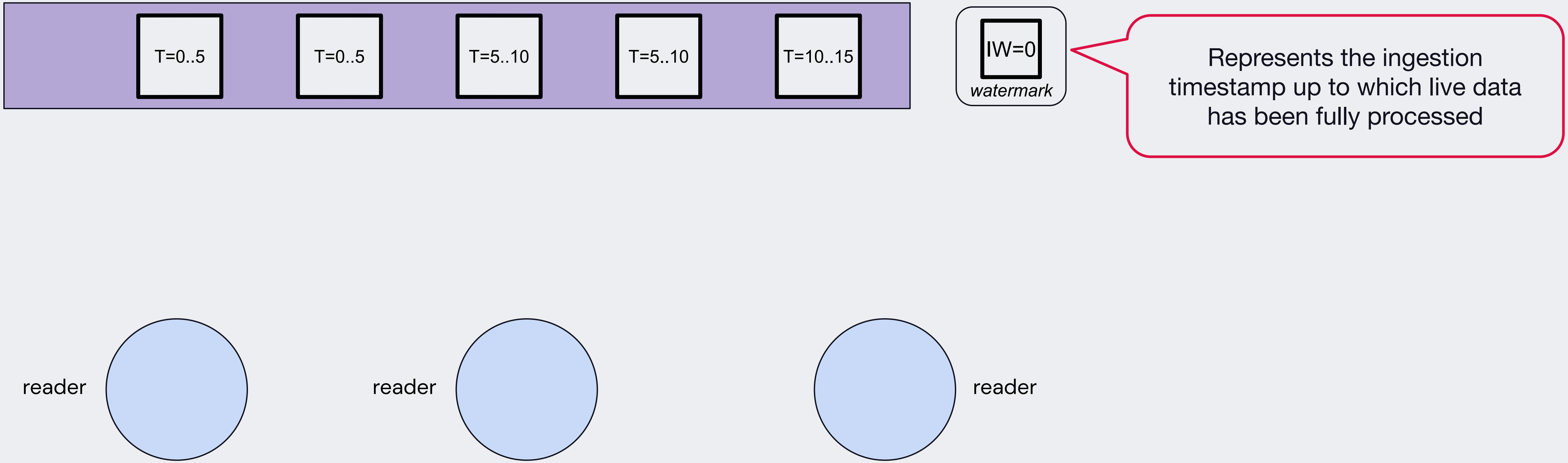


Solution: Use lateness tolerated by app



Assuming lateness of "10" minutes is okay.

Solution: Use lateness tolerated by app



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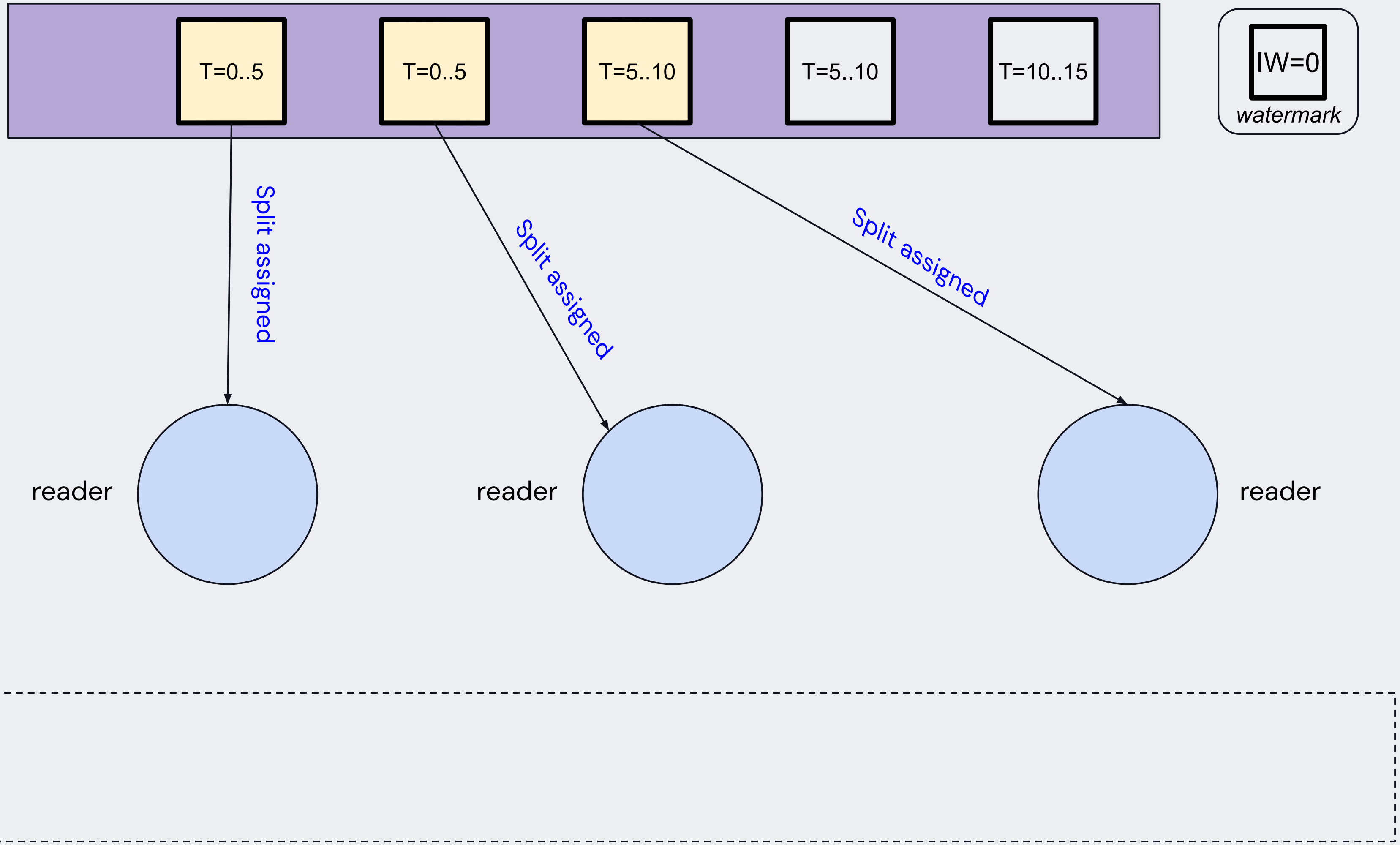

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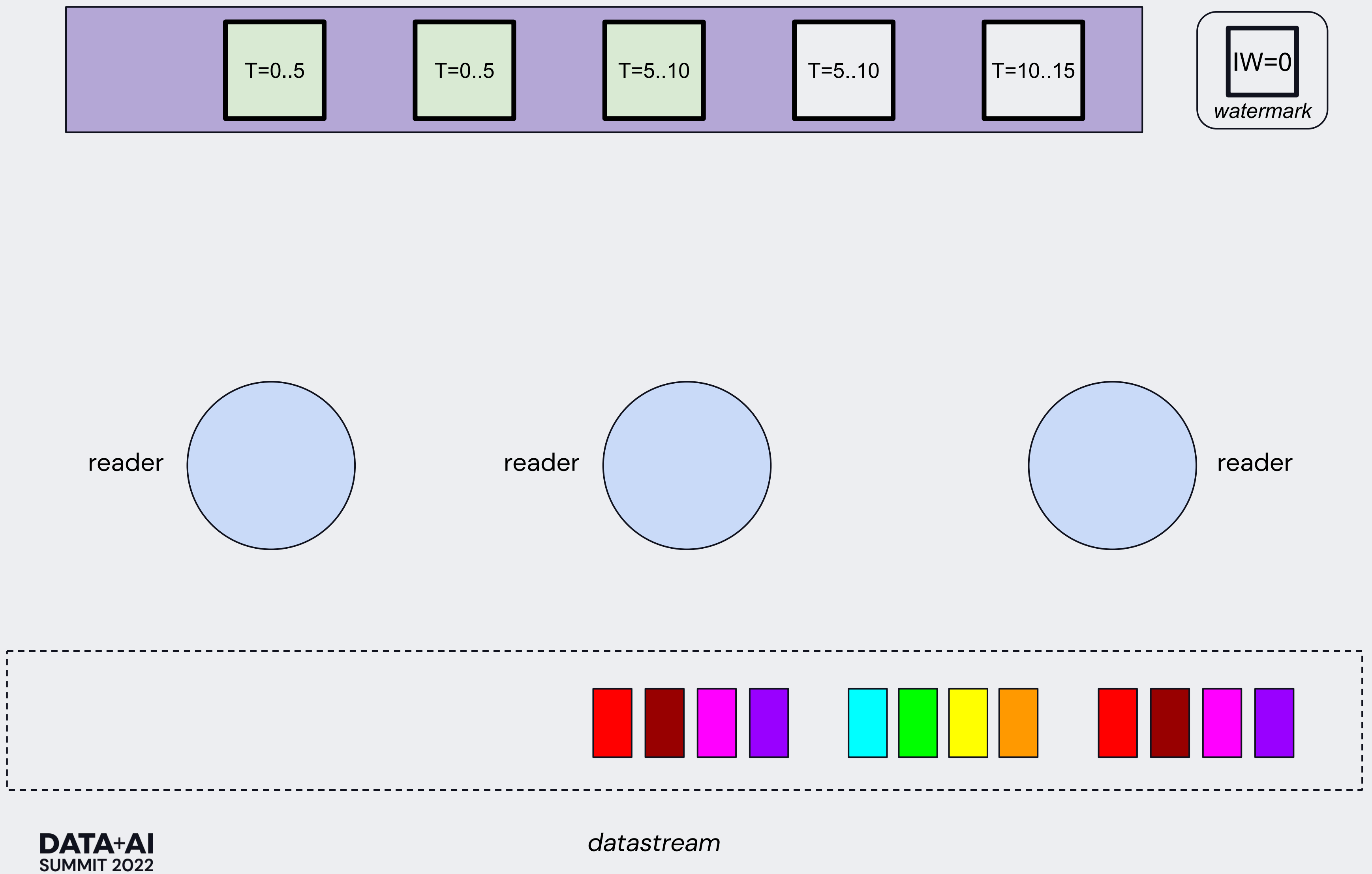

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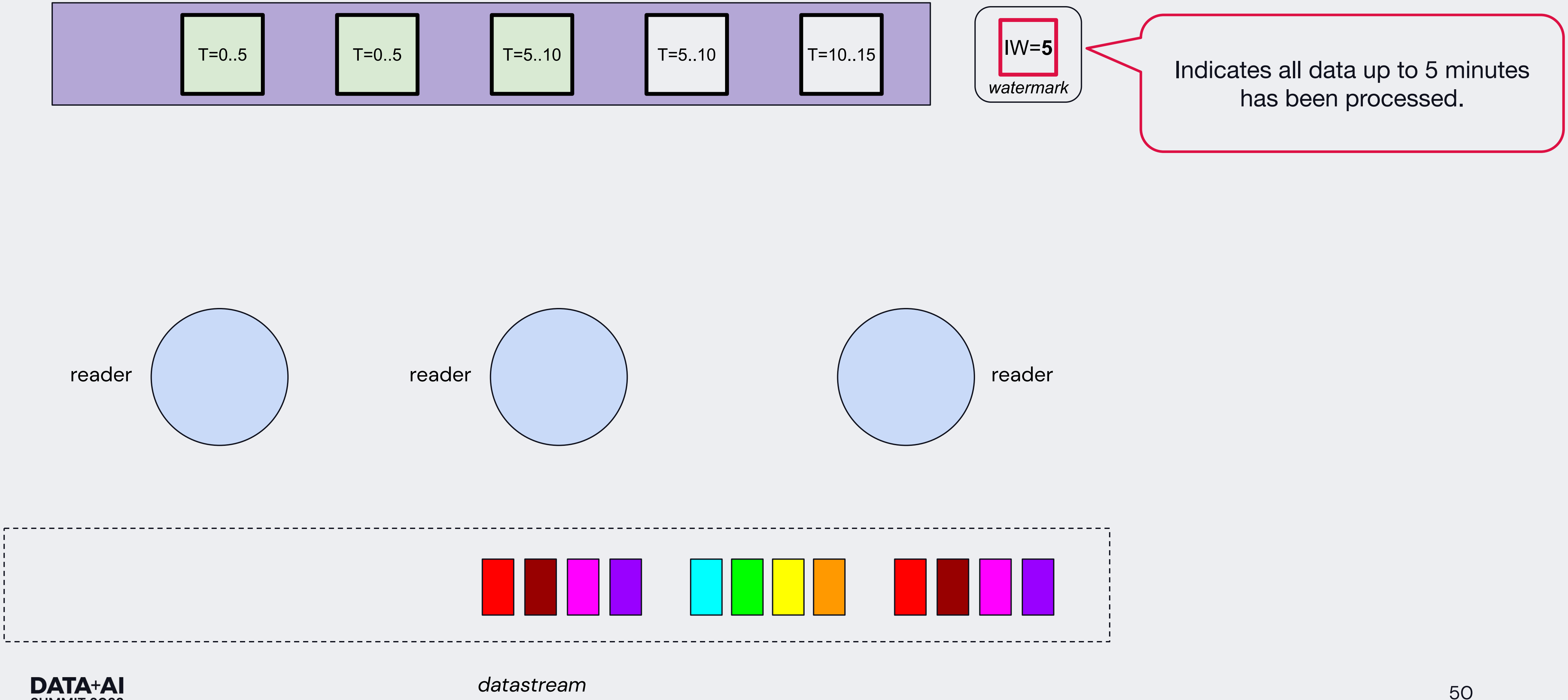

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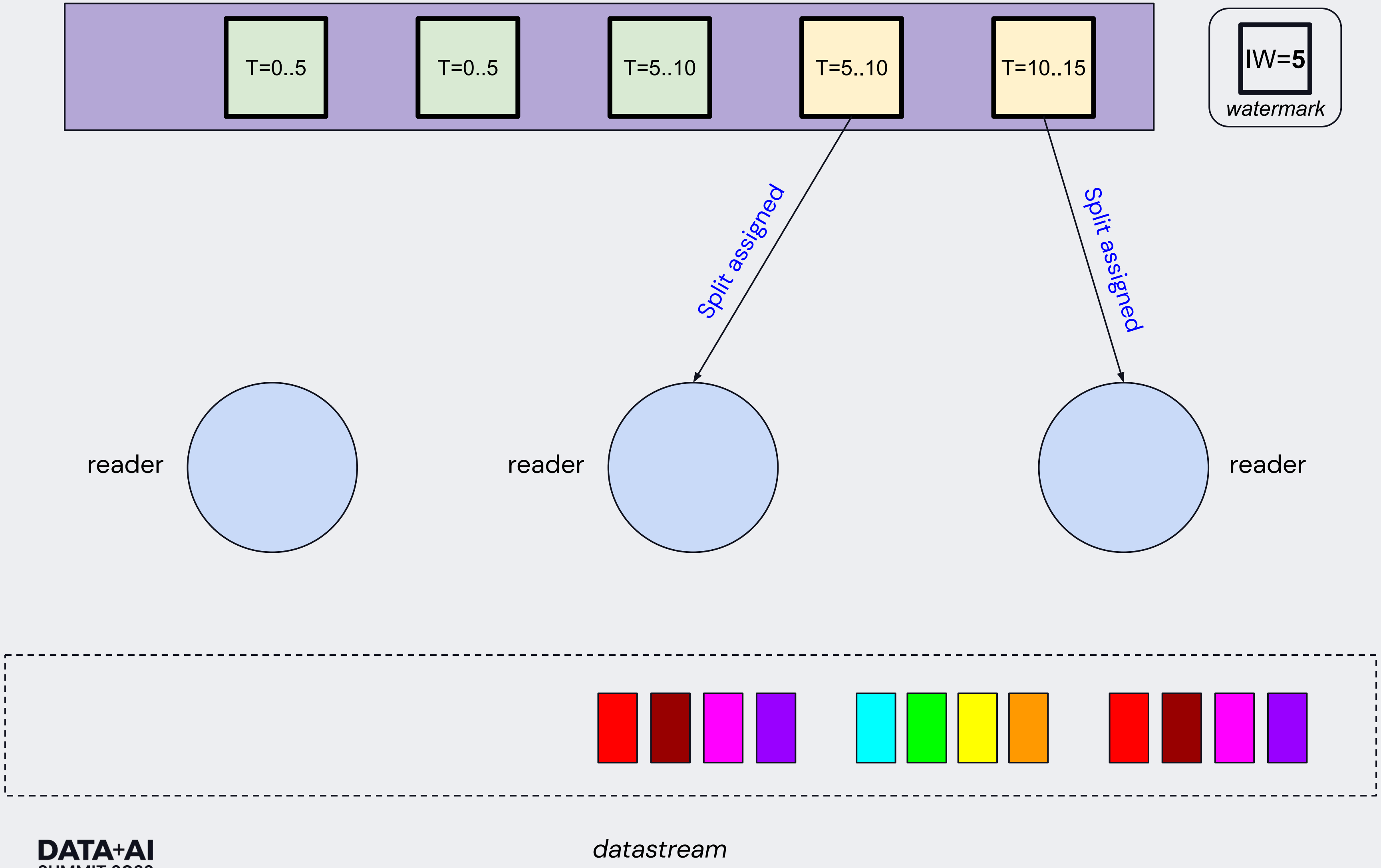


How to backfill?

- **Strawman 1:** Read events from files filtered by backfill dates
  - ✔ Scales horizontally to backfill quickly
  - ✖ Does not work for all types of applications
- **Strawman 2:** Order all files and read them in order
  - ✔ Guarantees similar ordering semantics as the live traffic
  - ✖ Does not scale horizontally
- **Our Solution:** Read files while maintaining lateness constraints
  - ✔ Guarantees ordering that work for the application
  - ✔ Scales horizontally to finish backfill quickly

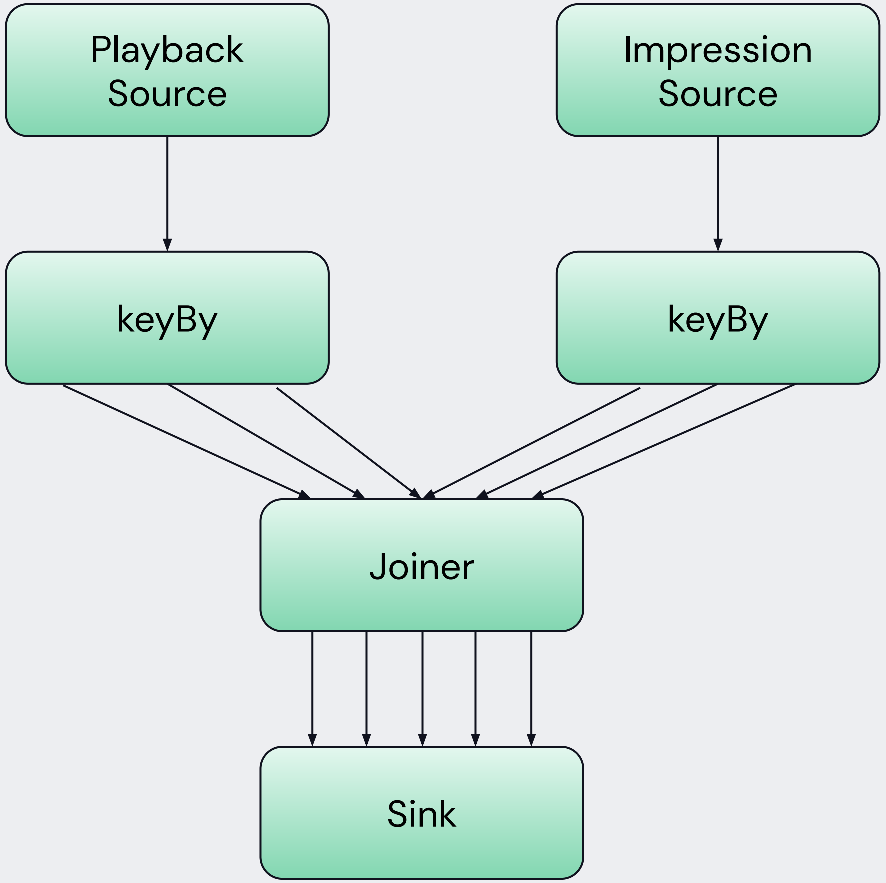
Messaging System's Ordering Guarantees

- Kafka provides strict ordering of events within a partition.

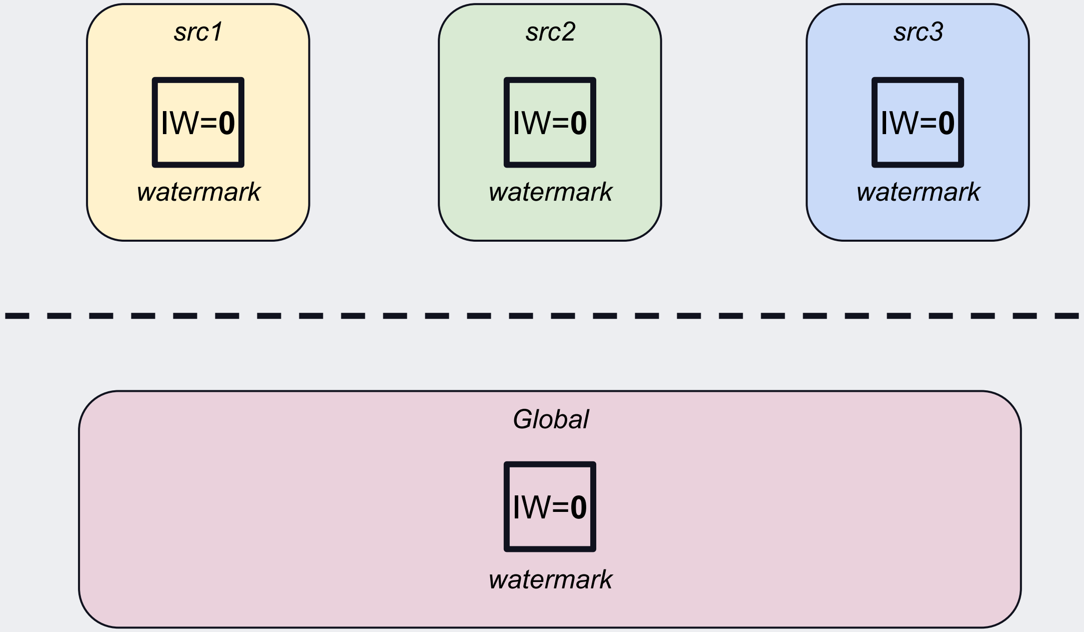
- Most analytical use-cases (streaming-joins, sessionization) use event-time semantics and do not require such stronger guarantees.

Challenge 2: Reading Multiple Sources

- One source can have significantly way more data than the other.
- During backfill, this could lead to a watermark skew resulting in state size explosion.
- This can eventually lead to slow checkpoints or checkpoint timeouts.



Solution: Coordinate watermarks



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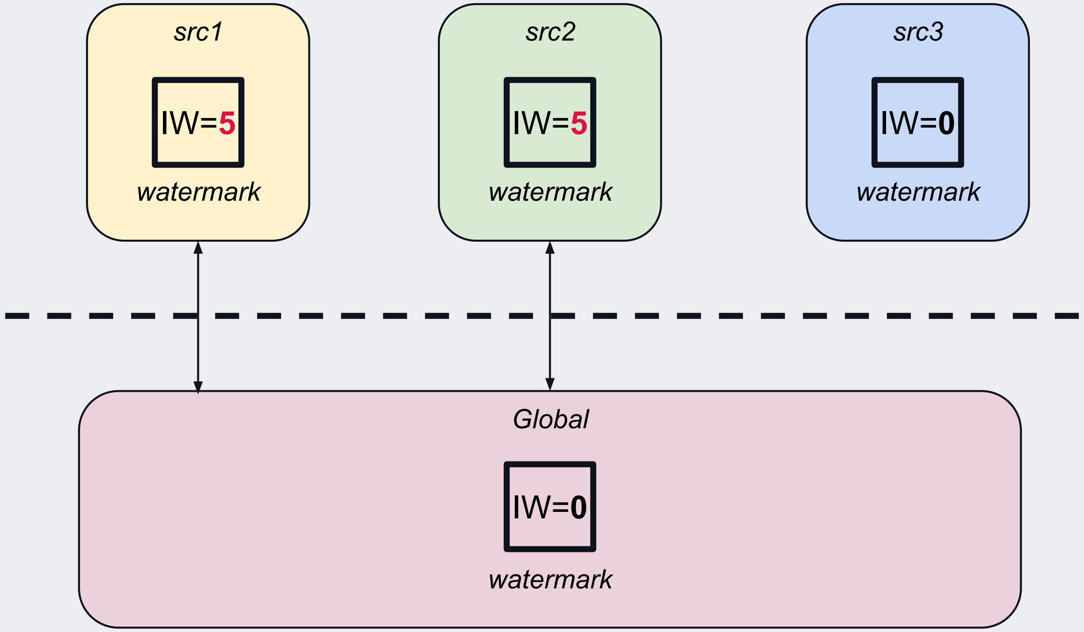
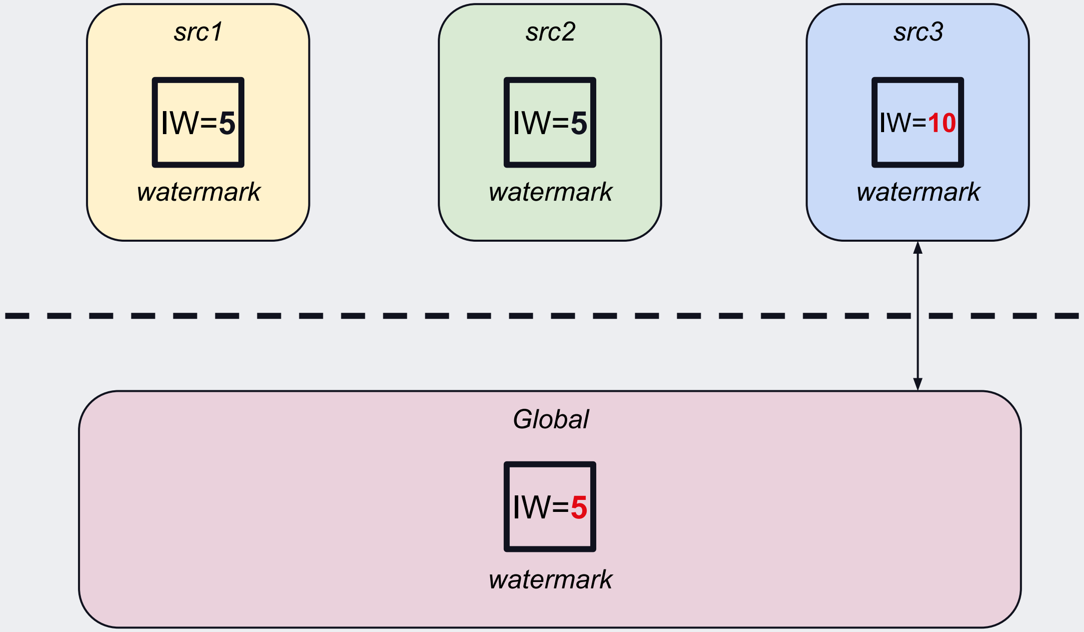


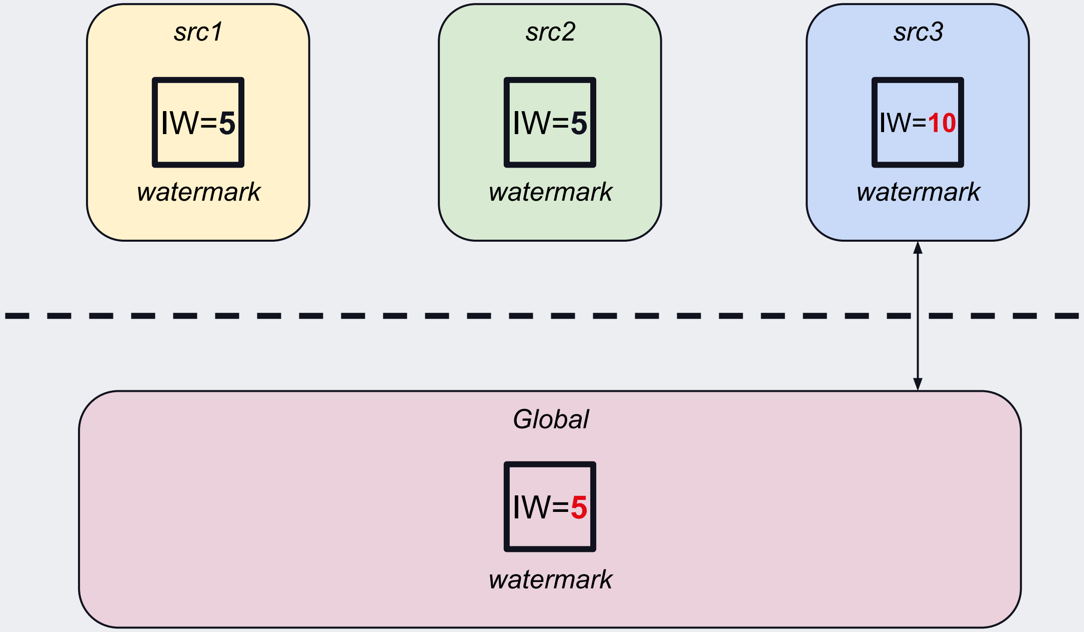
Communicate watermark updates to the global tracker.

Solution: Coordinate watermarks



Global watermark should reflect the slowest source.

Solution: Coordinate watermarks



Use the *global watermark* to find if files can be dispatched without violating the **'lateness'** constraint.

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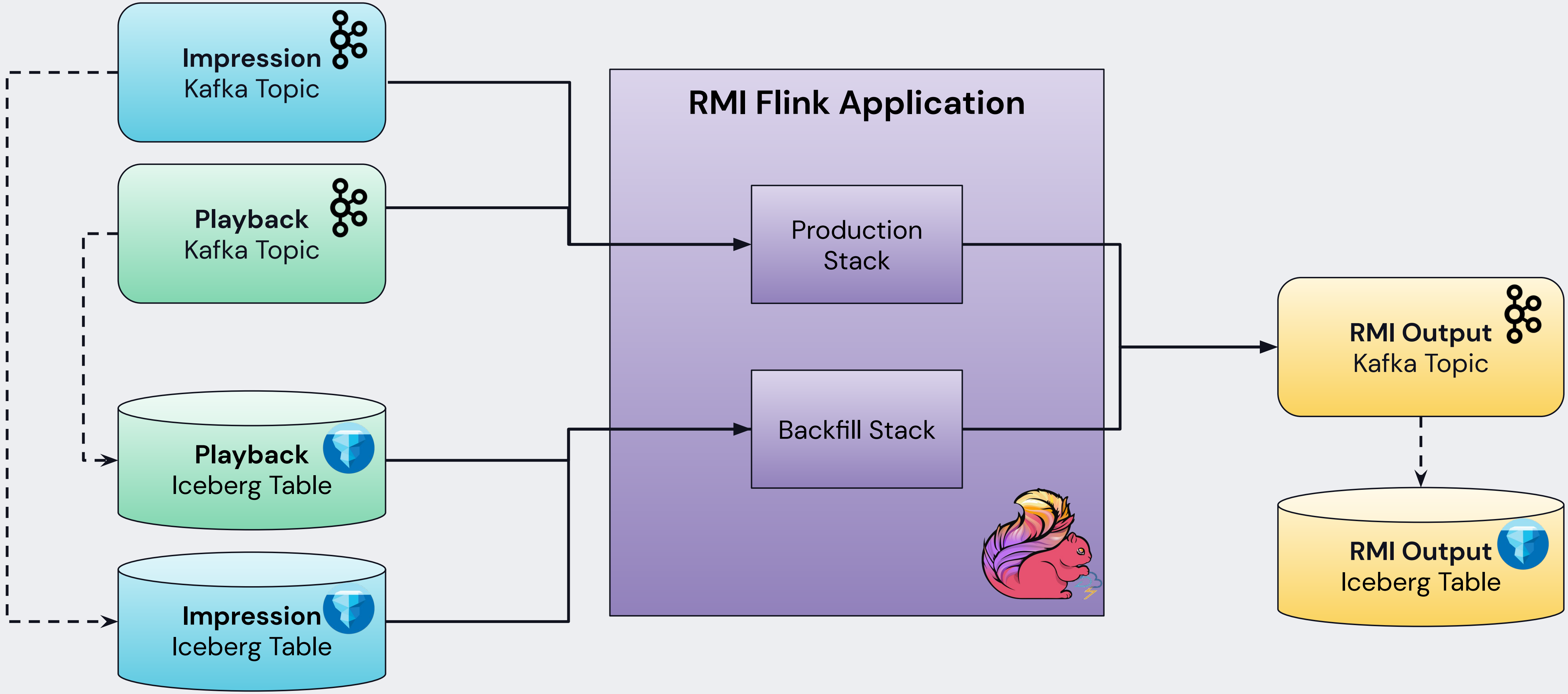
- **Our Solution:** Read files while maintaining lateness constraints
    - ✔ Guarantees ordering that work for the application
    - ✔ Scales horizontally to finish backfill quickly
    - ✔ Alignment across sources to avoid state size explosion

Agenda

- ❖ Why backfill streaming pipelines
- ❖ Existing approaches
- ❖ Backfill in Kappa Style using Data Lake
- ❖ Event ordering challenges
- ❖ **Adopting Kappa backfill**

Adopting Kappa Backfill



Adopting Kappa Backfill

Minimal code changes

```
@SpringBootApplication
class PersonlizationsStreamingApp {
  @Bean
  def flinkJob(
      @Source("impression-source") impressionSource: SourceBuilder[Record[ImpressionEvent]],
      @Source("playback-source") playbackSource: SourceBuilder[Record[PlaybackEvent]],
      @Sink("summary-sink") summarySink: SinkBuilder[ImpressionPlaySummary]) {...}

  @Bean
  def liveImpressionSourceConfigurer(): KafkaSourceConfigurer[Record[ImpressionEvent]] =
    new KafkaSourceConfigurer("live-impression-source", KafkaCirceDeserializer[ImpressionEvent])
}
```

Adopting Kappa Backfill

Minimal code changes

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  @Bean
  def backfillImpressionSourceConfigurer(): IcebergSourceConfigurer[Record[ImpressionEvent]] =
    new IcebergSourceConfigurer(
      "backfill-impression-source",
       Avro.deserializerFactory[ImpressionEvent])
}
```

Adopting Kappa Backfill

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```

Note: In-memory representation of the Iceberg source is consistent with the Kafka Source.

Adopting Kappa Backfill

Minimal code changes

```yaml
nfflink:
  job.name: rmi-app
  connectors:
    sources:
      impression-source:
        type: dynamic
        selected: live-impression-source
        candidates:
        - live-impression-source
        - backfill-impression-source
      live-impression-source:
        type: kafka
        topics: impressions
        cluster: impressions_cluster
      backfill-impression-source:
        type: iceberg
        database: default
        table: impression_table_name
        max_misalignment_threshold: 15min
```

App config changes to support backfilling

Adopting Kappa Backfill

What we learned from backfilling in prod

Results

- High throughput: processing 24 hours of data takes ~ 5 hours.
- Consistent data quality: backfill output matches 99.9% with prod.

Lessons Learned

- Backfilling window and configs depend on application logic.
- Backfilling job needs tuning (separately from prod job).

Kappa Backfill benefits

- 👏 Use the same streaming application for production and backfilling
- 👏 Easy to set up
- 👏 Backfill large historical data quickly
- 👏 Cost Efficient ($2M/year in Iceberg v.s $93M/year in Kafka)

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Thank you

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