



Google Cloud

Cloud Dataflow
Streaming Features

Agenda

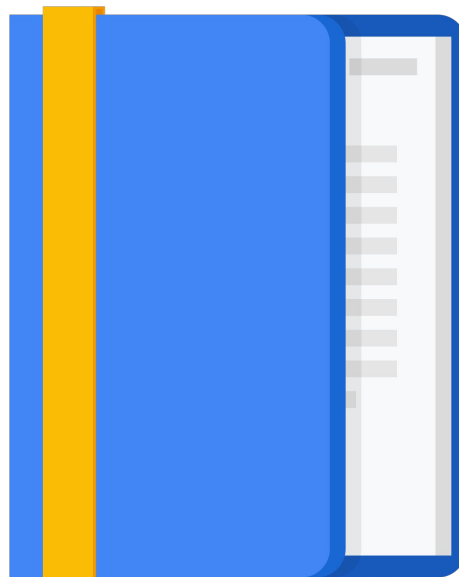
Processing Streaming Data

Cloud Pub/Sub

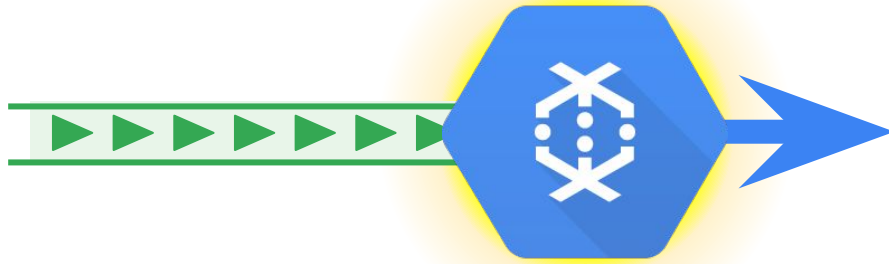
Cloud Dataflow Streaming
Features

BigQuery and Bigtable Streaming
Features

Advanced BigQuery Functionality



Streaming features of Cloud Dataflow



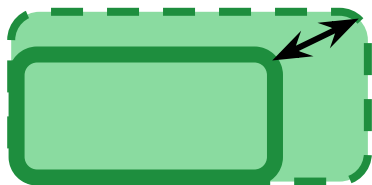
Cloud
Dataflow

Qualities that Cloud Dataflow
contributes to Data Engineering
solutions:

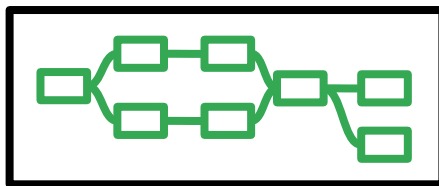
Scalability
Low latency

Continuing from the Data Processing course

Unbounded PCollection



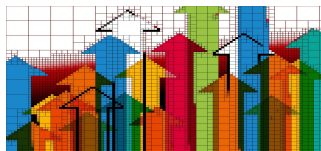
Pipeline



Streaming Jobs



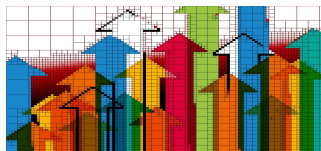
There are challenges with processing streaming data



Scalability

Streaming data generally only grows larger and more frequent

There are challenges with processing streaming data



Scalability

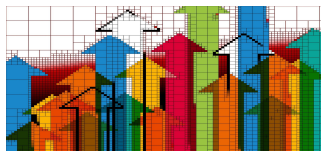
Streaming data generally only grows larger and more frequent



Fault Tolerance

Maintain fault tolerance despite increasing volumes of data

There are challenges with processing streaming data



Scalability

Streaming data generally only grows larger and more frequent



Fault Tolerance

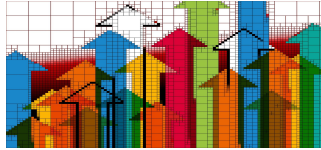
Maintain fault tolerance despite increasing volumes of data



Model

Is it streaming or repeated batch?

There are challenges with processing streaming data



Scalability

Streaming data generally only grows larger and more frequent



Fault Tolerance

Maintain fault tolerance despite increasing volumes of data



Model

Is it streaming or repeated batch?

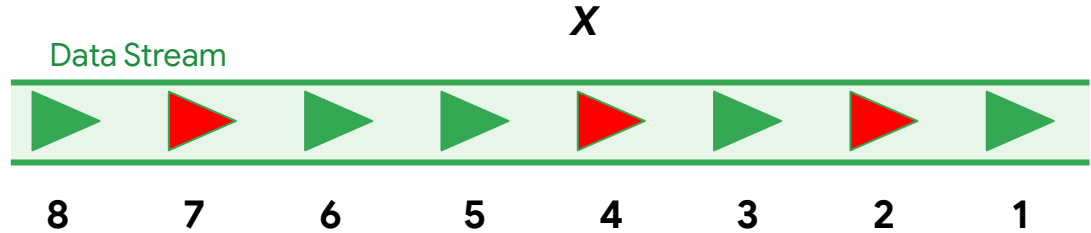


Timing

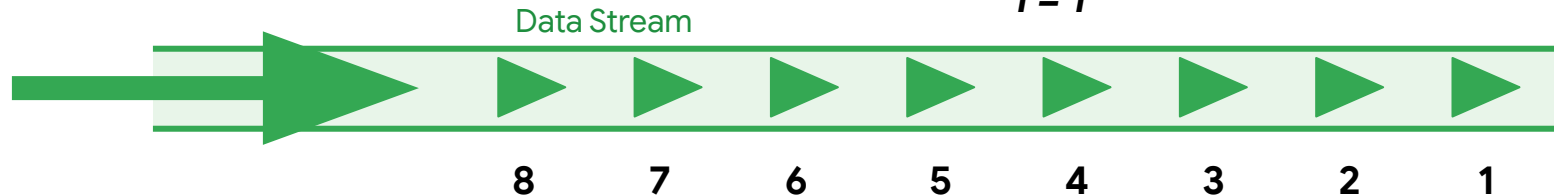
What if data arrives late?

How do you aggregate an unbounded set?

Filtering is straightforward



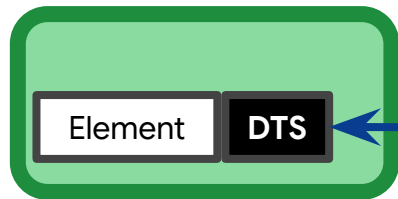
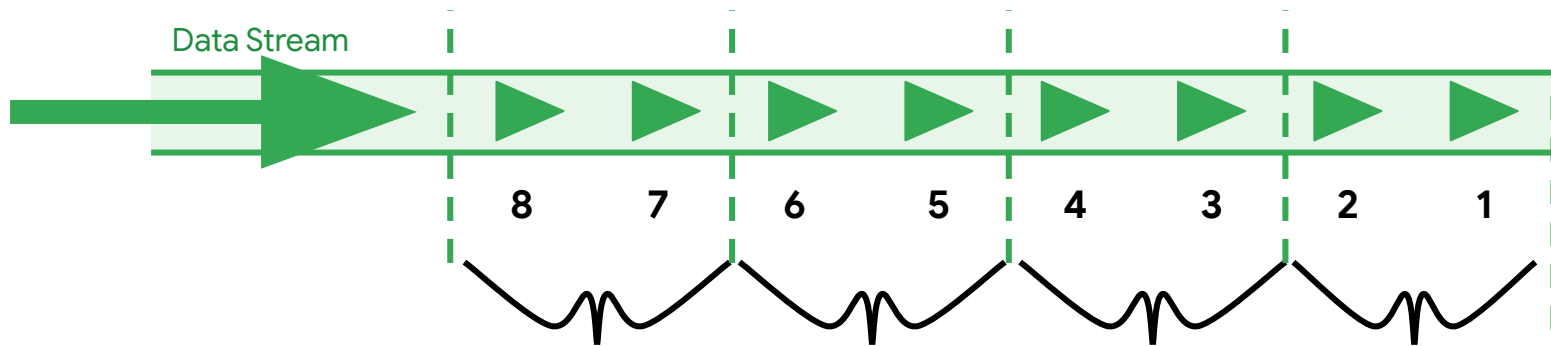
But how do you take an average on an unbounded stream of data?



$$\sum_{i=1}^n x_i$$

What is the stopping limit?

Divide the stream into a series of finite windows



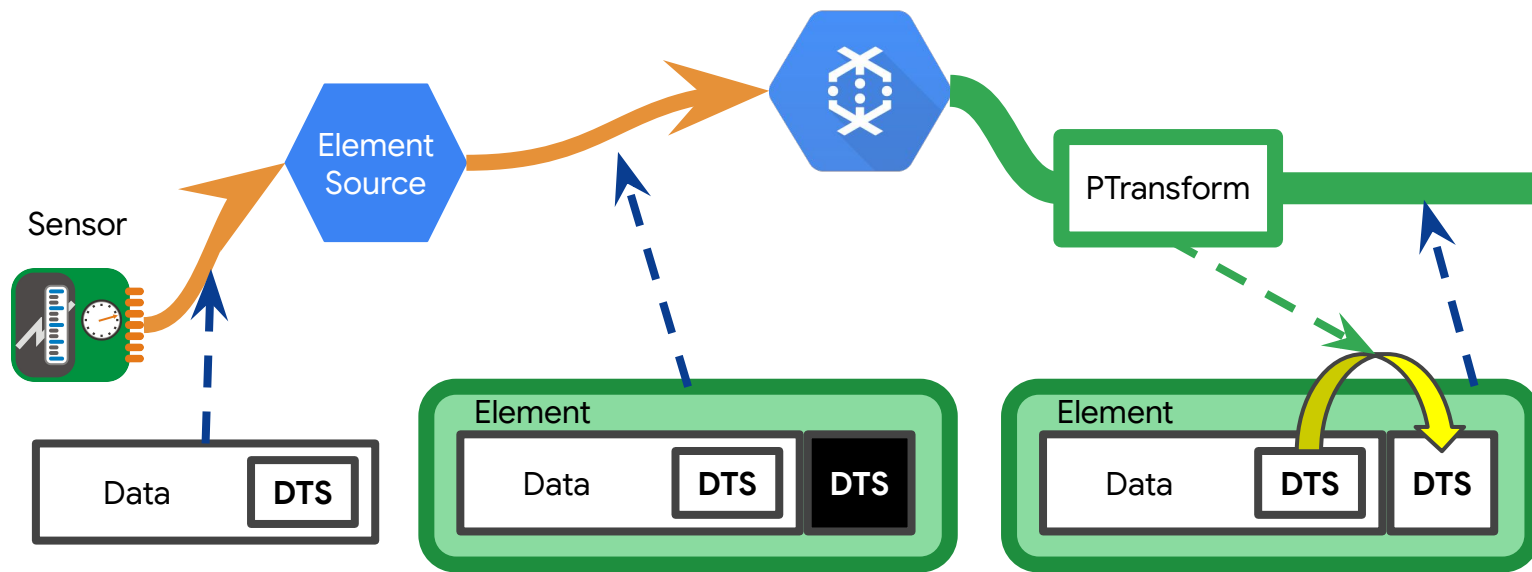
Windows are defined by element date-timestamp (metadata, usually Pub/Sub ingest time)

$$\sum_{i=w}^n x_i$$

$$\sum_{i=w}^n x_i$$

$$\sum_{i=w}^n x_i$$

Modify the date-timestamp with a PTransform if needed



Code to modify date-timestamp

Python

```
yield beam.window.TimestampedValue(element, unix_timestamp)
```

Java

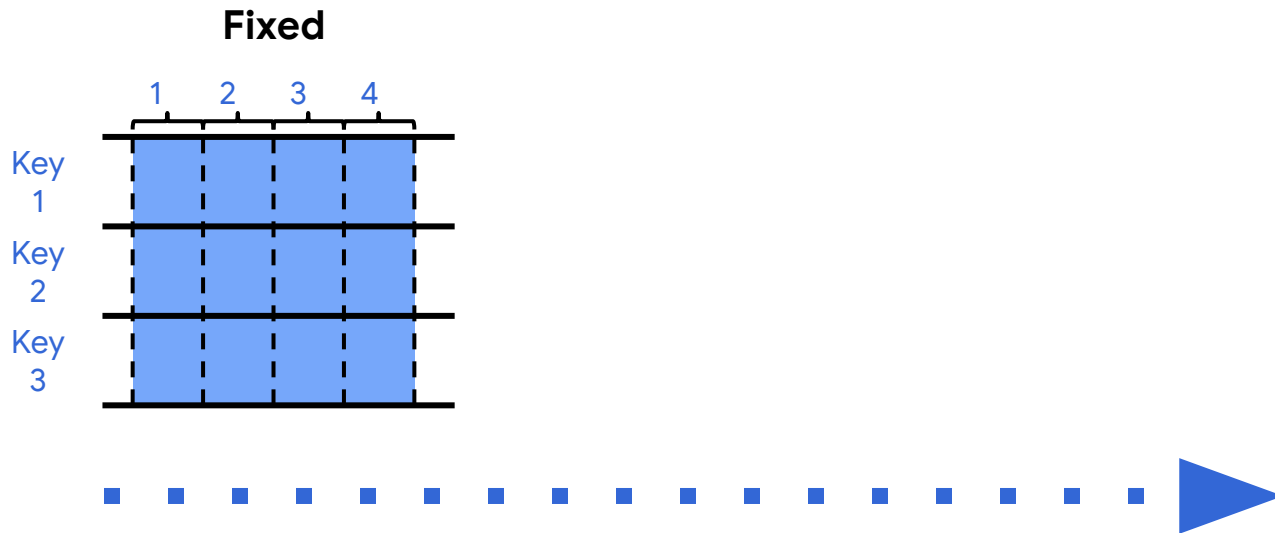
```
c.outputWithTimestamp (element, timestamp);
```

Cloud Dataflow Windowing

Three kinds of windows fit most circumstances

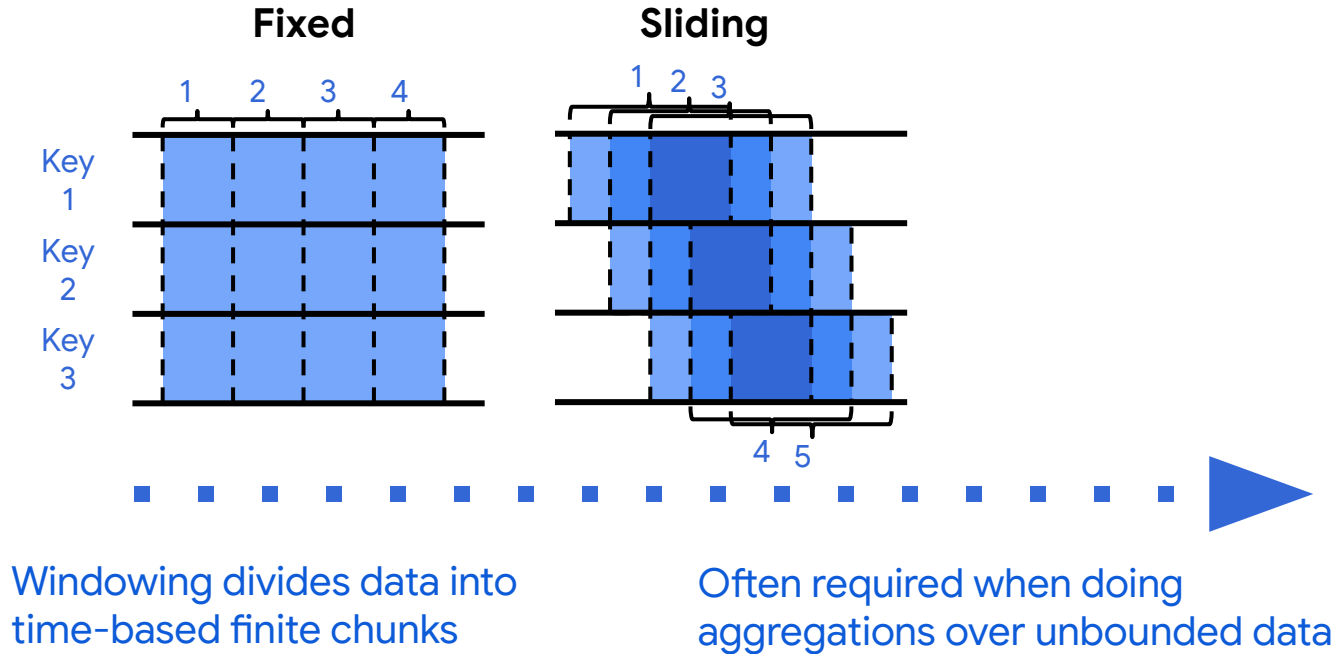
- Fixed
- Sliding
- Sessions

Three kinds of windows fit most circumstances

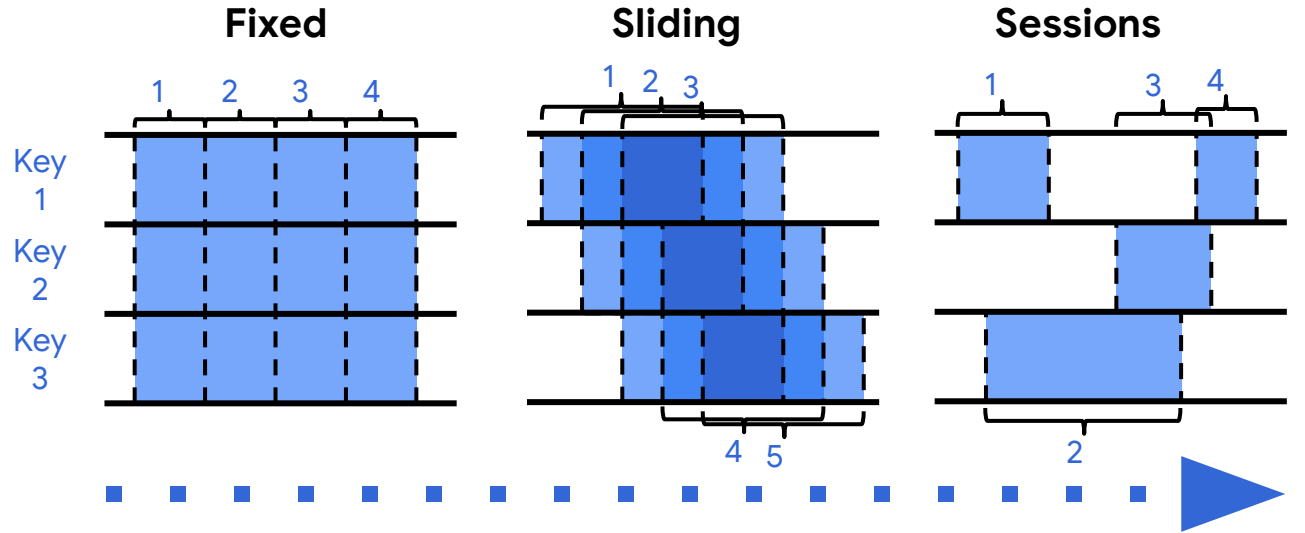


Windowing divides data into
time-based finite chunks

Three kinds of windows fit most circumstances



Three kinds of windows fit most circumstances



Windowing divides data into time-based finite chunks

Often required when doing aggregations over unbounded data

Setting time windows

Fixed-time windows

```
from apache_beam import window
fixed_windowed_items = (
    items | 'window' >> beam.WindowInto(window.FixedWindows(60)))
```

Python

Sliding time windows

```
from apache_beam import window
sliding_windowed_items = (
    items | 'window' >> beam.WindowInto(window.SlidingWindows(30, 5)))
```

Python

Session windows

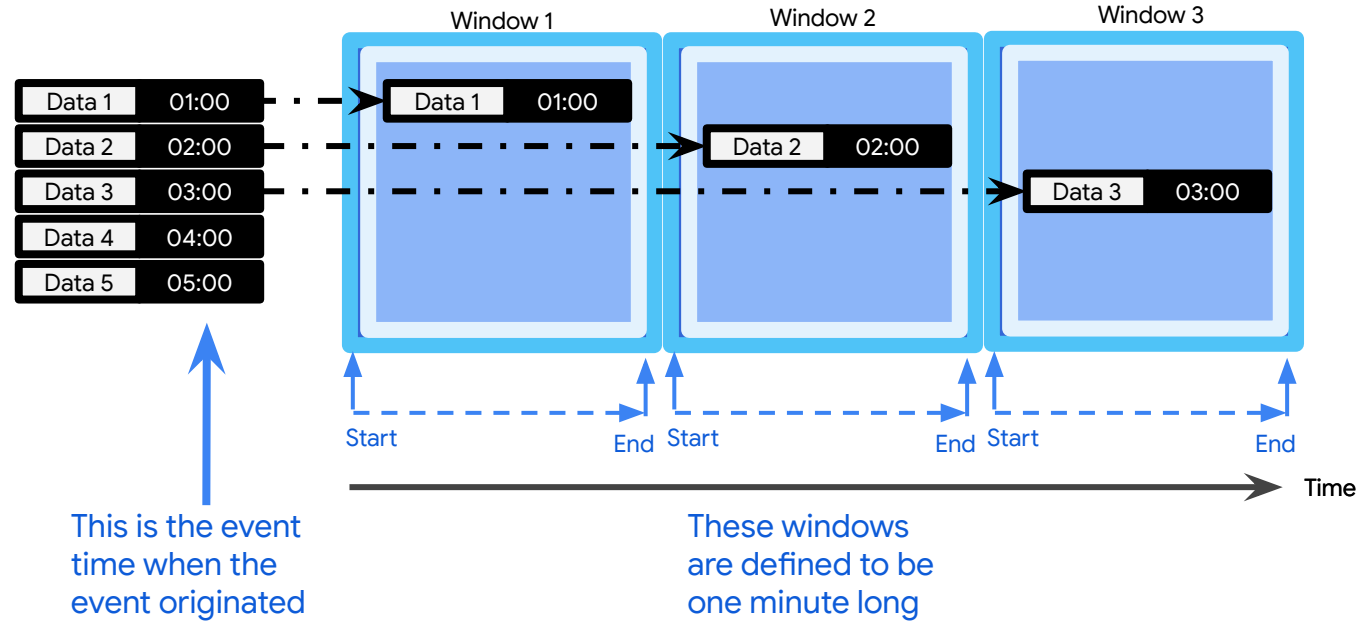
```
from apache_beam import window
session_windowed_items = (
    items | 'window' >> beam.WindowInto(window.Sessions(10 * 60)))
```

Python

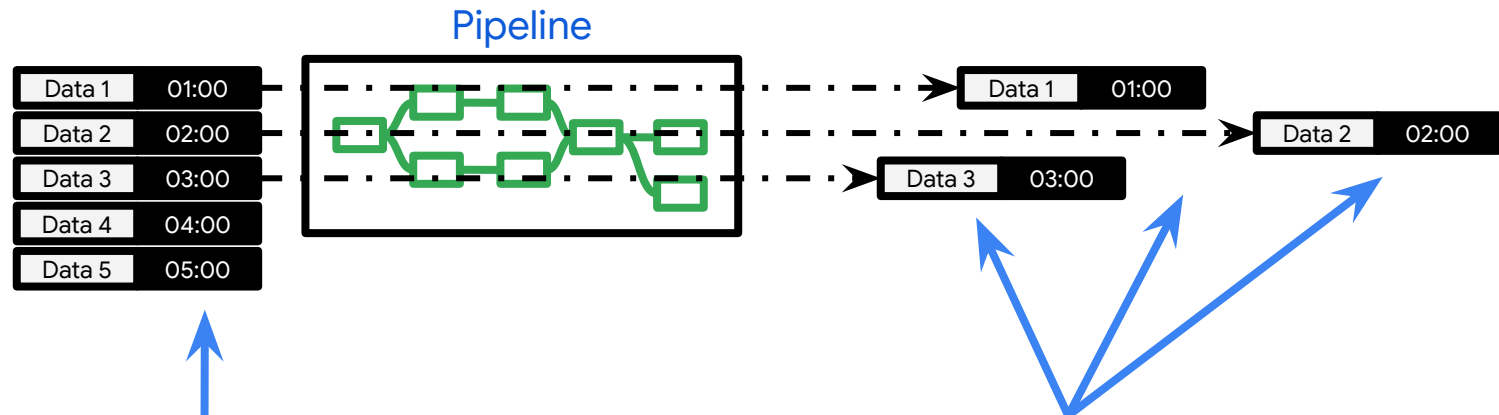
Remember:

you can apply windows to batch data, although you may need to generate the metadata date-timestamp on which windows operate.

Windowing by time if there is no latency



Pipeline processing can introduce latency



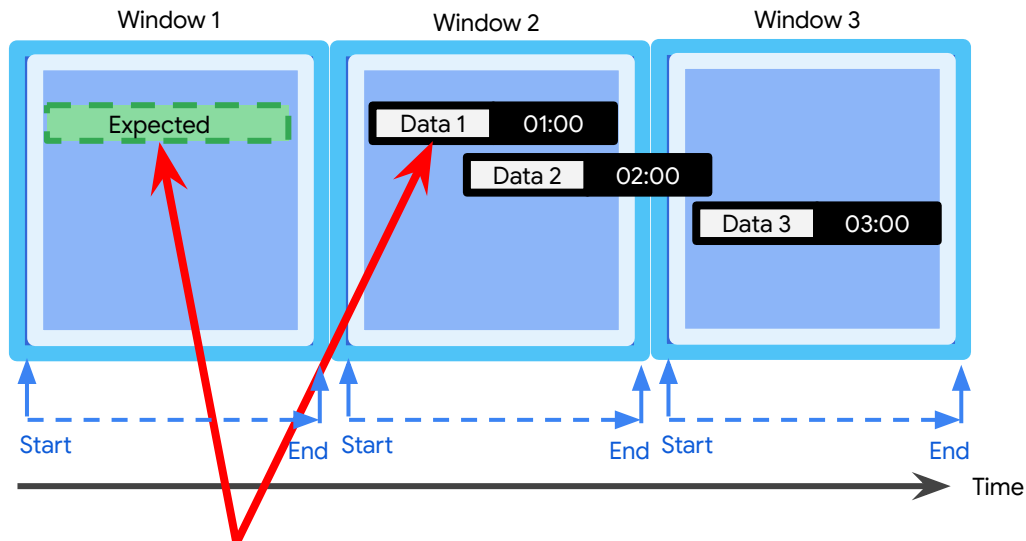
This is the event time when the event originated

The time relationships at origination are not preserved.

They are arriving later than anticipated. And some of them are outside the original 1 minute window.

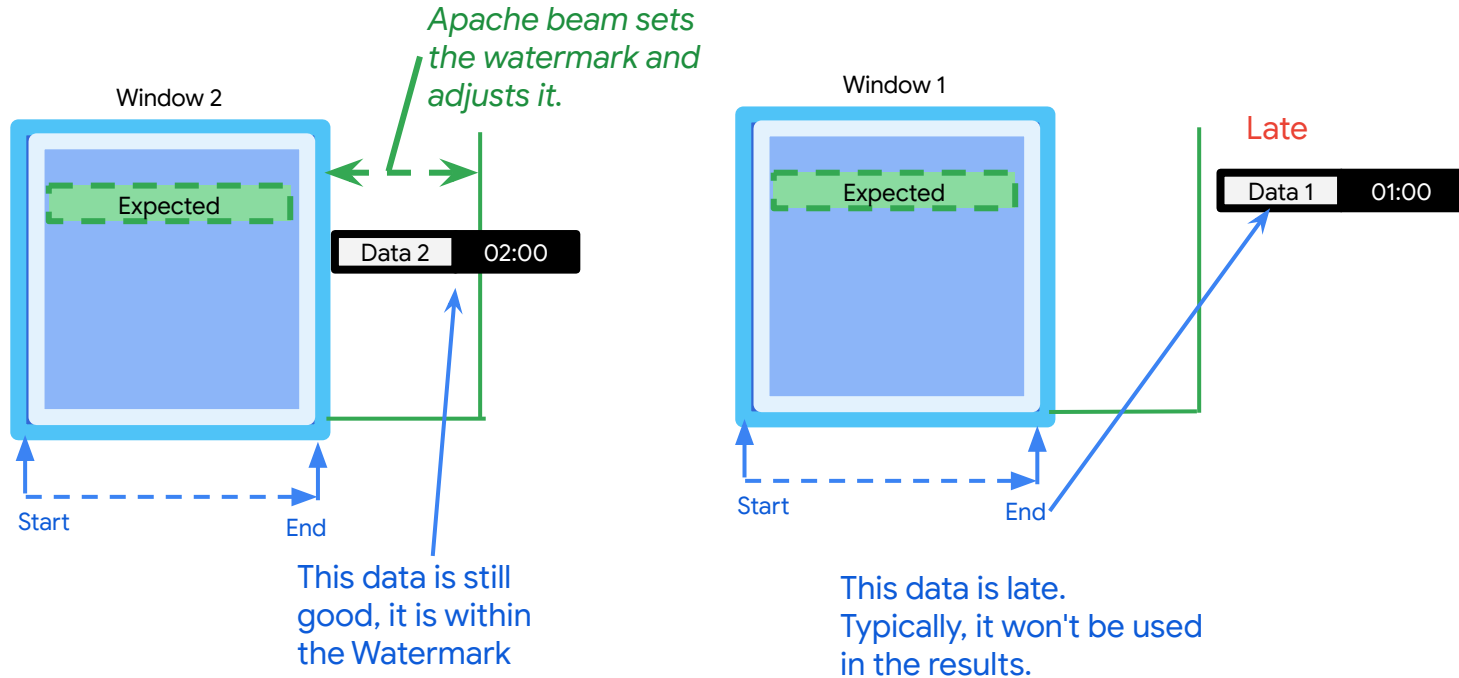
How should Cloud Dataflow deal with this situation?

The data could be a little past the window or a lot. Data 2 is a little outside of Window 2. Data 1 is completely outside of Window 1.

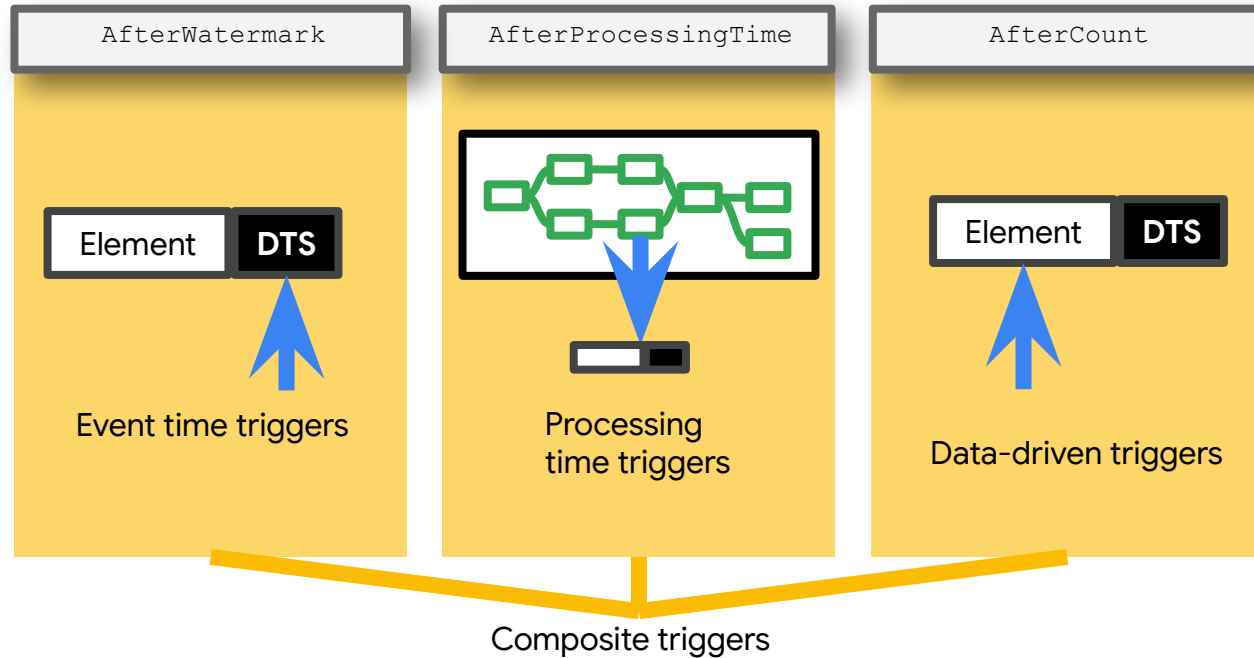


The difference in time from when data was expected to when it actually arrived is called the **lag time**.

Watermarks provide flexibility for a little lag time



The default is to trigger at the watermark, but we can also add custom trigger(s)



Some example triggers

```
pcollection | WindowInto(  
    SlidingWindows(60, 5),  
    trigger=AfterWatermark(  
        early=AfterProcessingTime(delay=30),  
        late=AfterCount(1))  
    accumulation_mode=AccumulationMode.ACCUMULATING)
```

Sliding window of 60 seconds, every 5 seconds
Relative to the watermark, trigger:
-- 30 seconds early
-- and for every late record (< allowedLateness)
the pane should have all the records

```
pcollection | WindowInto(  
    FixedWindows(60),  
    trigger=Repeatedly(  
        AfterAny(  
            AfterCount(100),  
            AfterProcessingTime(1 * 60))),  
    accumulation_mode=AccumulationMode.DISCARDING)
```

Fixed window of 60 seconds
Set up a composite trigger that triggers ...
whenever either of these happens:
-- 100 elements accumulate
-- every 60 seconds (ignore watermark)
the trigger should be with only new records

You can allow late data past the watermark in Java

Allowing Late Data

```
PCollection<String> items = ...;
```

Java

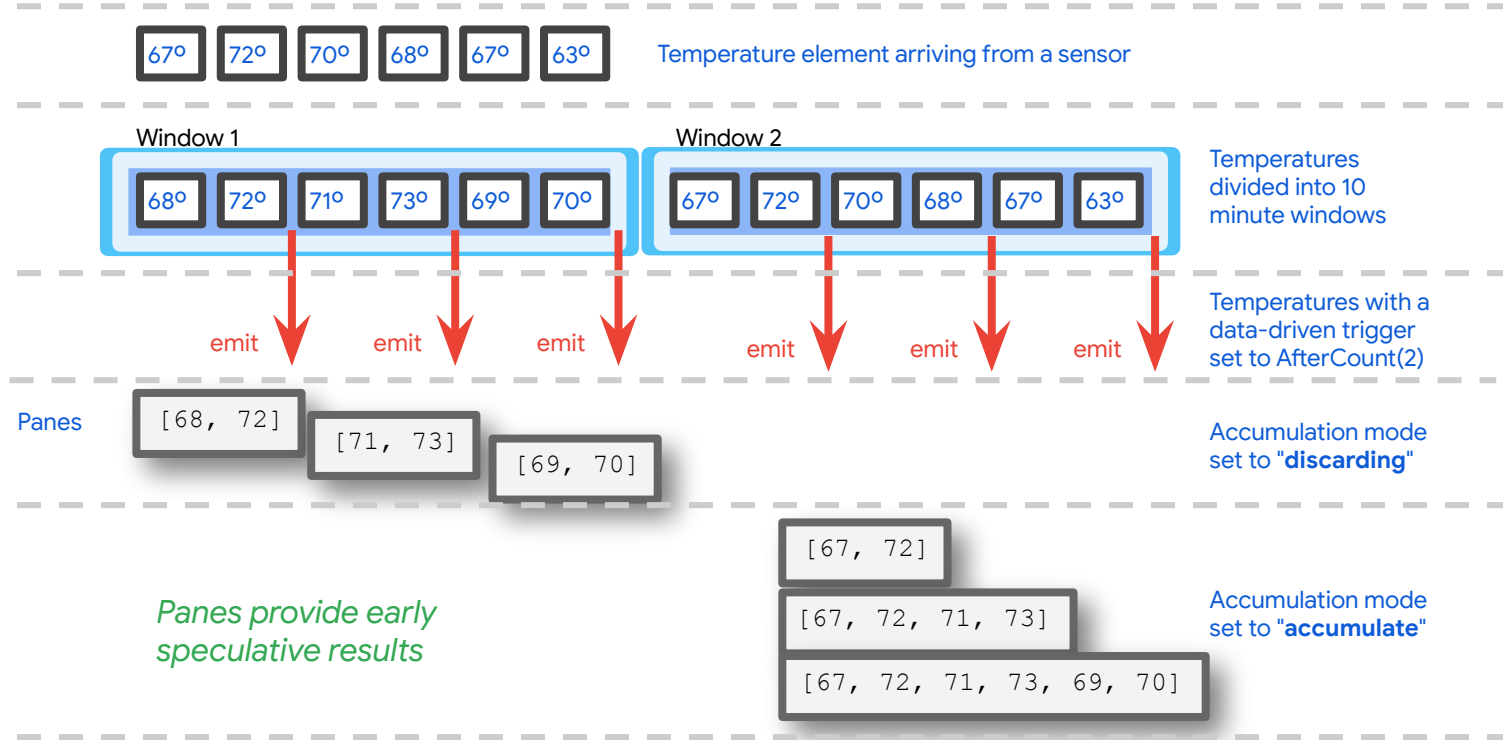
```
PCollection<String> fixedWindowedItems = items.apply(  
    Window.<String>into(FixedWindows.of(Duration.standardMinutes(1)))  
    .withAllowedLateness(Duration.standardDays(2)));
```

Python

Not supported for Python at this time.

That means 100% of late data is just discarded. And features designed to do something with late data simply do not work in a Python pipeline.

Accumulation modes: what to do with additional events





Streaming Data Pipelines

Objectives

- Launch Dataflow and run a Dataflow job
- Understand how data elements flow through the transformations of a Dataflow pipeline
- Connect Dataflow to Pub/Sub and BigQuery
- Observe and understand how Dataflow autoscaling adjusts compute resources to process input data optimally
- Learn where to find logging information created by Dataflow
- Explore metrics and create alerts and dashboards with Stackdriver Monitoring