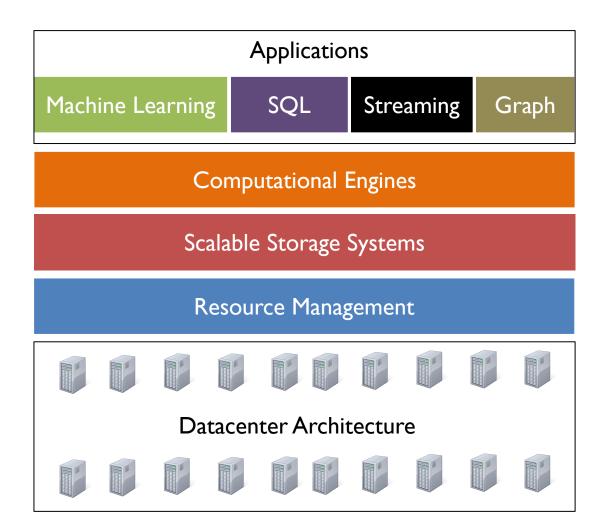
#### CS 744: DATAFLOW

Shivaram Venkataraman Fall 2019

#### **ADMINISTRIVIA**

- Assignment 2 grades up
- Midterm grading
- Course project proposal comments
- AEFIS feedback

No Class next Tuesday?



DATAFLOW MODEL (?)

#### **MOTIVATION**

#### Streaming Video Provider

- How much to bill each advertiser?
- Need per-user, per-video viewing sessions
- Handle out of order data

#### Goals

- Easy to program
- Balance correctness, latency and cost

#### **APPROACH**

#### **API** Design

Separate user-facing model from execution

Decompose queries into

- What is being computed
- Where in time is it computed
- When is it materialized
- How does it relate to earlier results

#### **TERMINOLOGY**

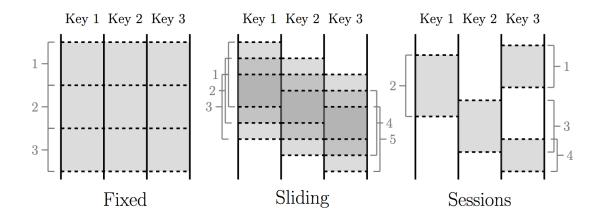
Unbounded/bounded data
Streaming/Batch execution

Timestamps

Event time:

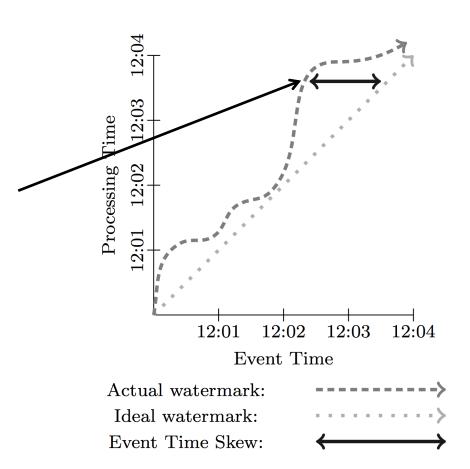
Processing time:

# WINDOWING



#### WATERMARK OR SKEW

System has processed all events up to 12:02:30



#### API

ParDo:

GroupByKey:

Windowing AssignWindow

MergeWindow

# **EXAMPLE**

```
(k_1, v_1, 13:02, [0, \infty)),
    (k_2, v_2, 13:14, [0, \infty)),
    (k_1, v_3, 13.57, [0, \infty)),
    (k_1, v_4, 13:20, [0, \infty))
                   AssignWindows(Sessions(30m))
(k_1, v_1, 13:02, [13:02, 13:32)),
(k_2, v_2, 13:14, [13:14, 13:44)),
(k_1, v_3, 13.57, [13.57, 14.27)),
(k_1, v_4, 13:20, [13:20, 13:50))
                    DropTimestamps
   (k_1, v_1, [13:02, 13:32)),
    (k_2, v_2, [13:14, 13:44)),
   (k_1, v_3, [13:57, 14:27)),
    (k_1, v_4, [13:20, 13:50))
                                       GroupByKey
```

```
(k_1, [(v_1, [13:02, 13:32)),
            (v_3, [13:57, 14:27)),
           (v_4, [13:20, 13:50))]),
     (k_2, [(v_2, [13:14, 13:44))])
                       MergeWindows(Sessions(30m))
     (k_1, [(v_1, [13:02, 13:50)),
            (v_3, [13:57, 14:27)),
          (v_4, [13:02, 13:50))]),
     (k_2, [(v_2, [13:14, 13:44))])
                    (k_1, [([\mathbf{v_1}, \mathbf{v_4}], [13:02, 13:50)),
         ([\mathbf{v_3}], [13:57, 14:27))]),
    (k_2, [([\mathbf{v_2}], [13:14, 13:44))])
                      ExpandToElements
(k_1, [v_1, v_4], \mathbf{13:50}, [13:02, 13:50)),
  (k_1, [v_3], \mathbf{14:27}, [13:57, 14:27)),
```

 $(k_2, [v_2], \mathbf{13:44}, [13:14, 13:44))$ 

#### TRIGGERS AND INCREMENTAL PROCESSING

Windowing: where in event time data are grouped

Triggering: when in processing time groups are emitted

#### Strategies

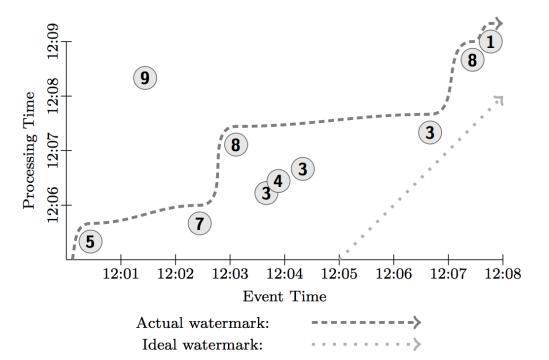
Discarding

Accumulating

Accumulating & Retracting

#### RUNNING EXAMPLE

```
PCollection<KV<String, Integer>> input = I0.read(...);
PCollection<KV<String, Integer>> output =
    input.apply(Sum.integersPerKey());
```



## GLOBAL WINDOWS, ACCUMULATE

12:04

Event Time

12:05

12:07

12:08

12:06

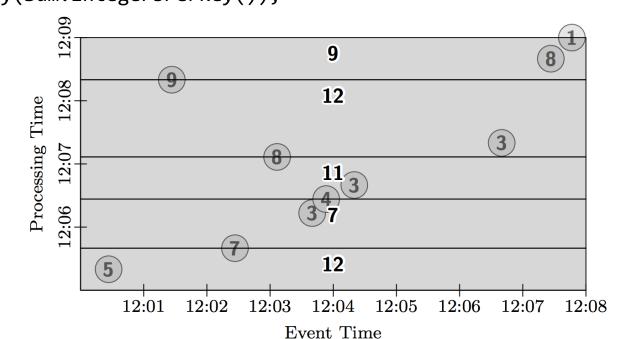
```
PCollection<KV<String, Integer>> output = input
     .apply(Window.trigger(Repeat(AtPeriod(1, MINUTE)))
                    .accumulating())
     .apply(Sum.integersPerKey());
                  12:09
                                              51
                                                                     8
                             9
                  12:08
               Processing Time
                                              33
                  2:07
                  12:06
                                              12
```

12:01

12:02

12:03

## GLOBAL WINDOWS, COUNT, DISCARDING



## FIXED WINDOWS, MICRO BATCH

Event Time

```
PCollection<KV<String, Integer>> output = input
     .apply(Window.into(FixedWindows.of(2, MINUTES))
                     .trigger(Repeat(AtWatermark())))
                     .accumulating())
                12:09
                                                                  12
                        14
                           9
                2:08
             Processing Time
                                                                  3
                                      22
                2:07
                                      14
14
                                                    3
                2:06
                         5
                     5
                       12:01
                              12:02
                                     12:03
                                            12:04
                                                  12:05
                                                         12:06
                                                                12:07
                                                                       12:08
```

#### LESSONS / EXPERIENCES

Don't rely on completeness

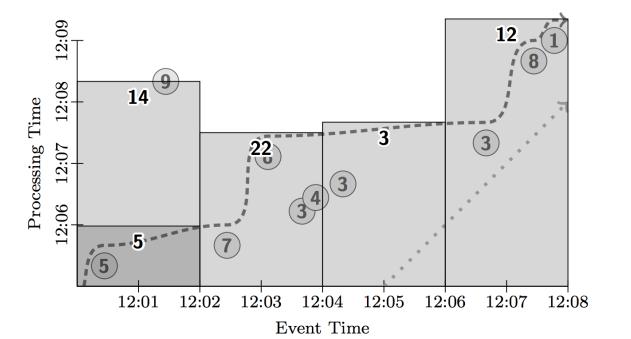
Be flexible, diverse use cases

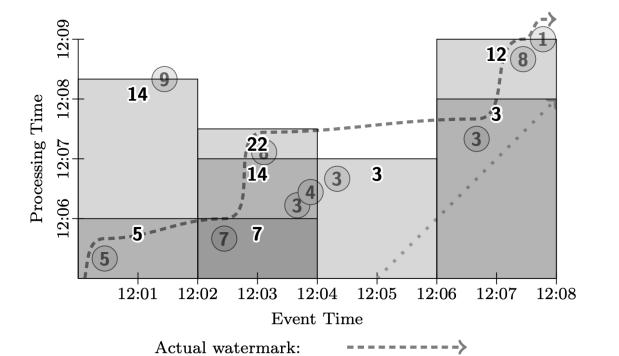
- Billing
- Recommendation
- Anomaly detection

Support analysis in context of events

# **DISCUSSION**

https://forms.gle/s7T2r67BDvkGQhmN9





Ideal watermark:

Consider you are implementing a micro-batch streaming API on top of Apache Spark. What are some of the bottlenecks/challenges you might have in building

such a system?