

# CS 744: BIG DATA SYSTEMS

Shivaram Venkataraman

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# ADMINISTRIVIA

- Assignment 2 grades up, Midterm grades this week
- Course Projects: round 2 meetings (Sign up!)
- Next Tuesday: Guest speaker for first part

**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

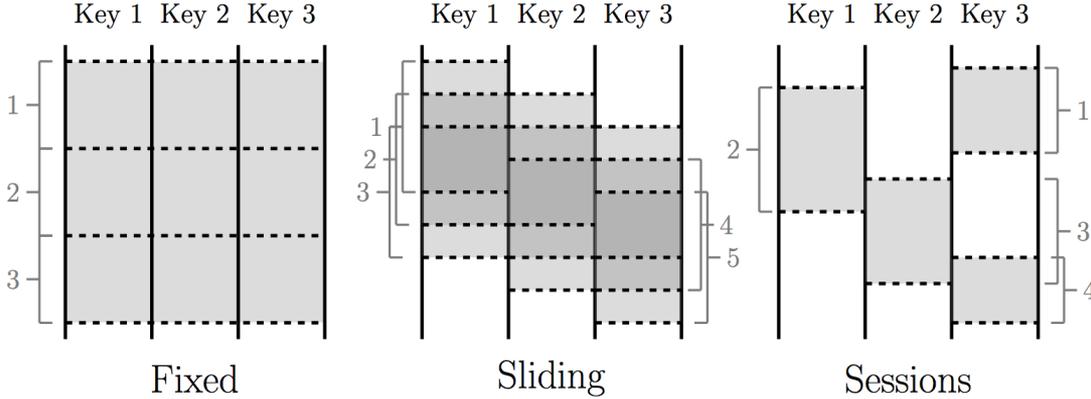
e.g., Flink vs. Spark Streaming

Timestamps

Event time:

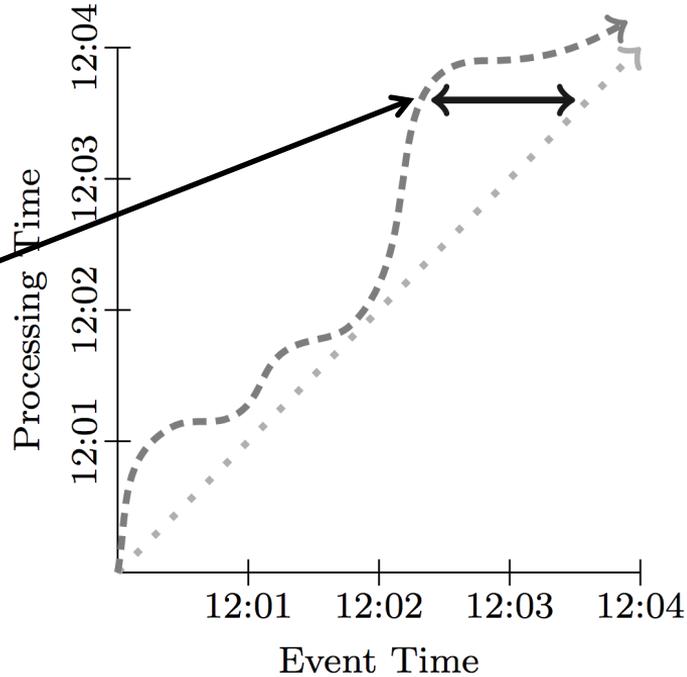
Processing time:

Window types



# WATERMARK OR SKEW

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



- Actual watermark: 
- Ideal watermark: 
- Event Time Skew: 

# API

ParDo: Parallel Do (very similar to map or flatMap)

GroupByKey: Group values for a key

Windowing

AssignWindow – Bucket tuple as it arrives

MergeWindow – Merge buckets based on grouping strategy

# 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))

$(k_1, [(v_1, [13:02, 13:50)),$   
     $(v_3, [13:57, 14:27)),$   
     $(v_4, [13:02, 13:50))])$ ,  
 $(k_2, [(v_2, [13:14, 13:44))])$

↓ *GroupAlsoByWindow*

$(k_1, [( [v_1, v_4], [13:02, 13:50)),$   
     $( [v_3], [13:57, 14:27))])$ ,  
 $(k_2, [( [v_2], [13:14, 13:44))])$

↓ *ExpandToElements*

$(k_1, [v_1, v_4], 13:50, [13:02, 13:50))$ ,  
 $(k_1, [v_3], 14:27, [13:57, 14:27))$ ,  
 $(k_2, [v_2], 13:44, [13:14, 13:44))$

# TRIGGERS AND INCREMENTAL PROCESSING

Windowing: **where** in event time data are grouped

Triggering: **when** in processing time groups are emitted

## Strategies

- Discarding

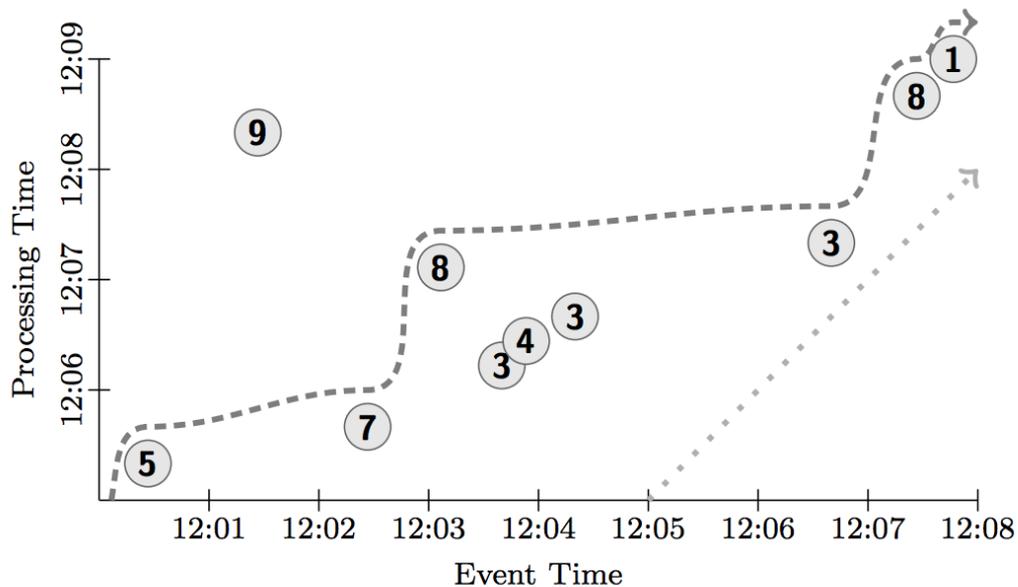
- Accumulating

- Accumulating & Retracting

Details with running example

# RUNNING EXAMPLE

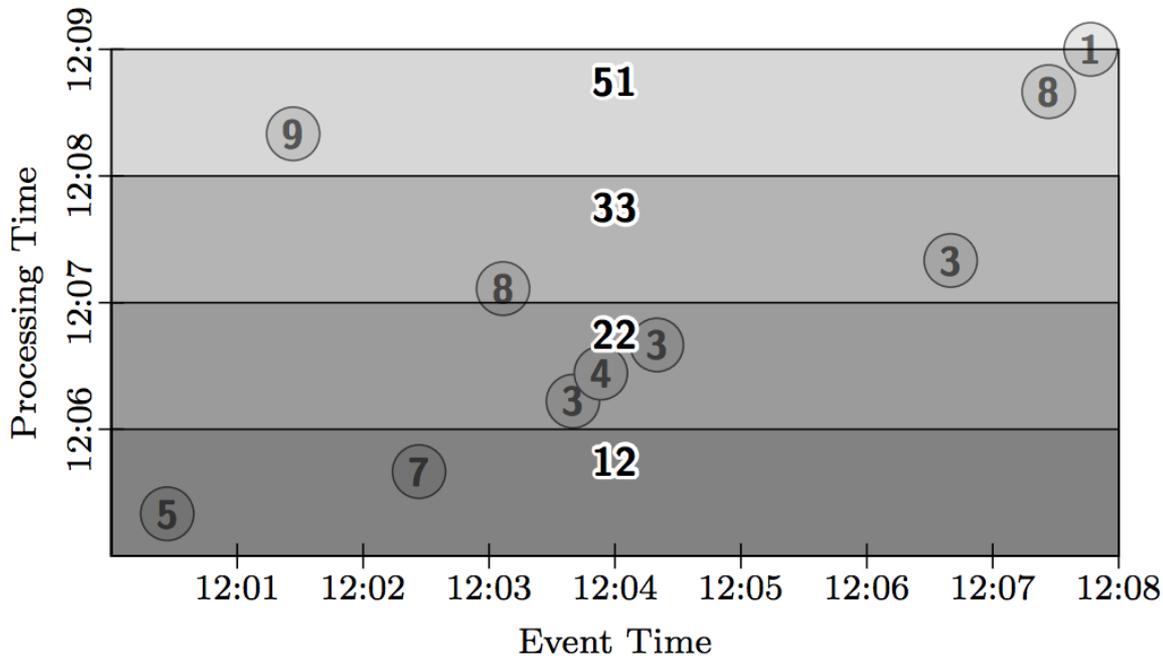
```
PCollection<KV<String, Integer>> input = IO.read(...);  
PCollection<KV<String, Integer>> output =  
    input.apply(Sum.integersPerKey());
```



Actual watermark:      ----->  
Ideal watermark:        .....>

# GLOBAL WINDOWS, ACCUMULATE

```
PCollection<KV<String, Integer>> output = input  
    .apply(Window.trigger(Repeat(AtPeriod(1, MINUTE))))  
        .accumulating()  
    .apply(Sum.integersPerKey());
```



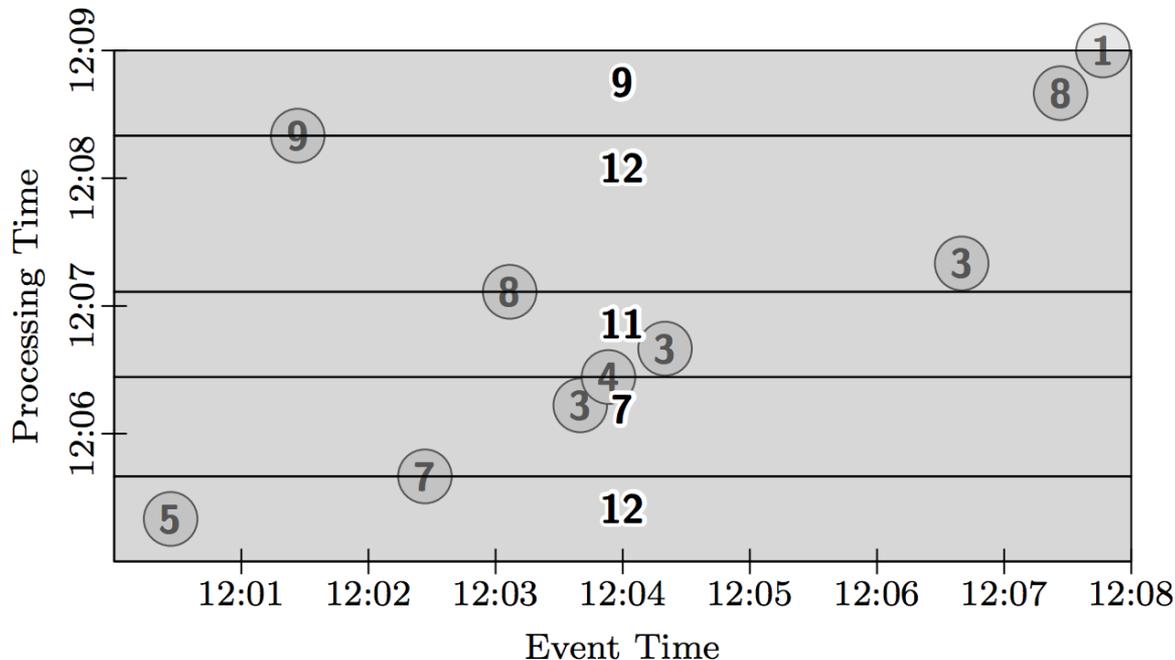
# GLOBAL WINDOWS, COUNT, DISCARDING

```
PCollection<KV<String, Integer>> output = input
```

```
    .apply(Window.trigger(Repeat(AtCount(2))))
```

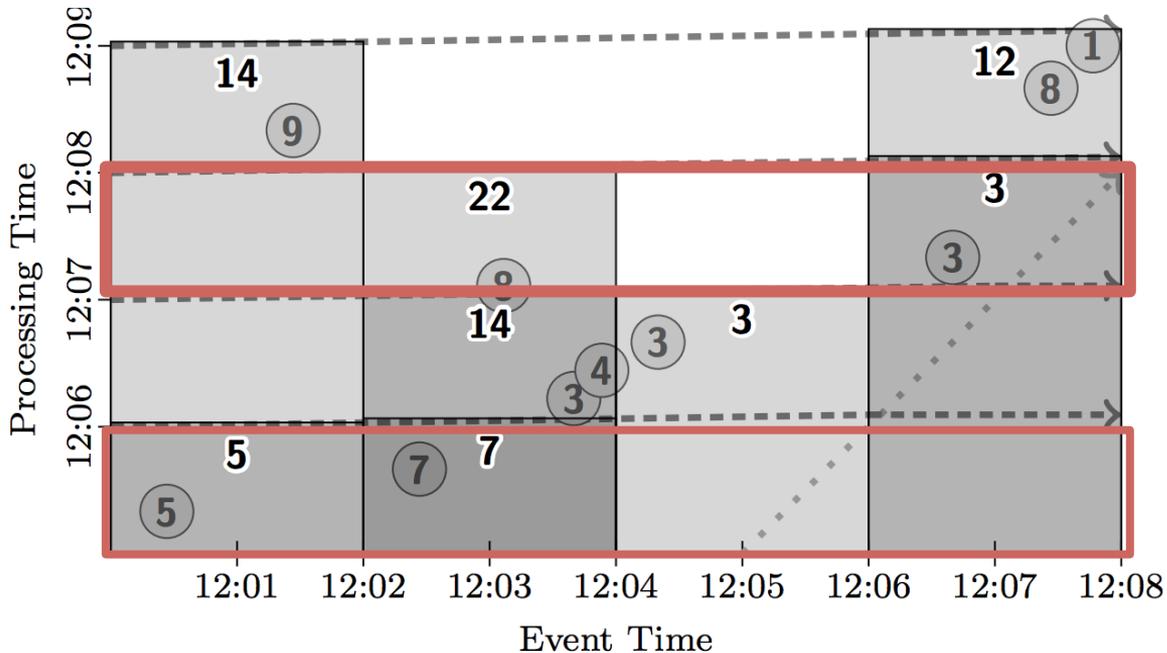
```
        .discarding()
```

```
    .apply(Sum.integersPerKey());
```



# FIXED WINDOWS, MICRO BATCH

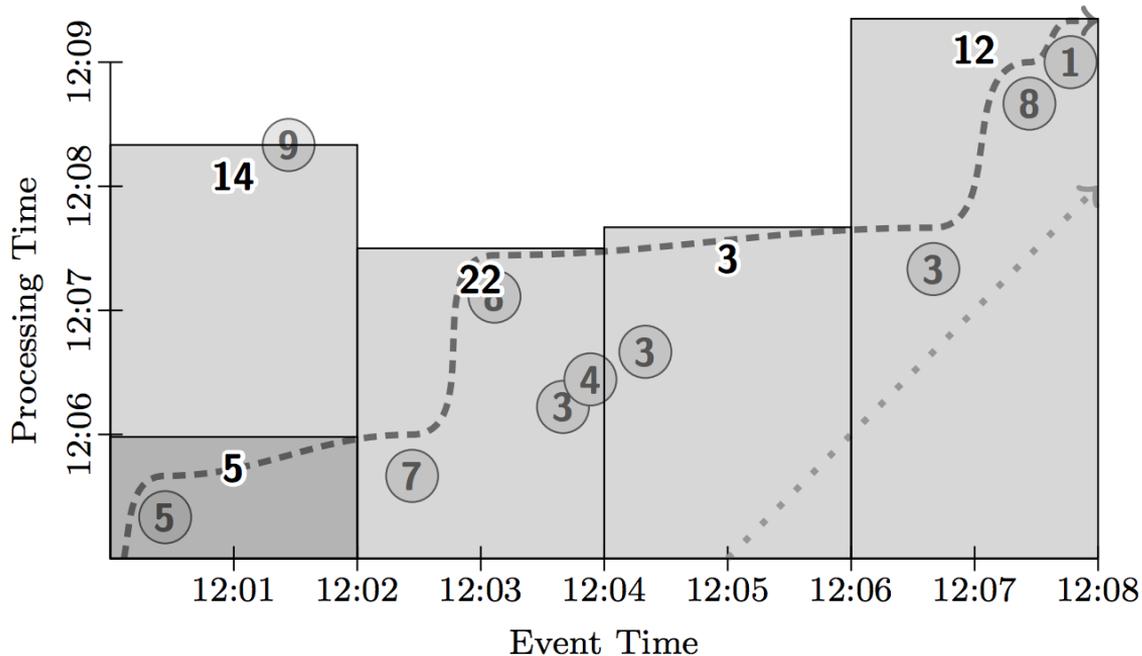
```
PCollection<KV<String, Integer>> output = input  
  .apply(Window.into(FixedWindows.of(2, MINUTES))  
    .trigger(Repeat(AtWatermark()))  
    .accumulating())
```



# FIXED WINDOWS, STREAMING

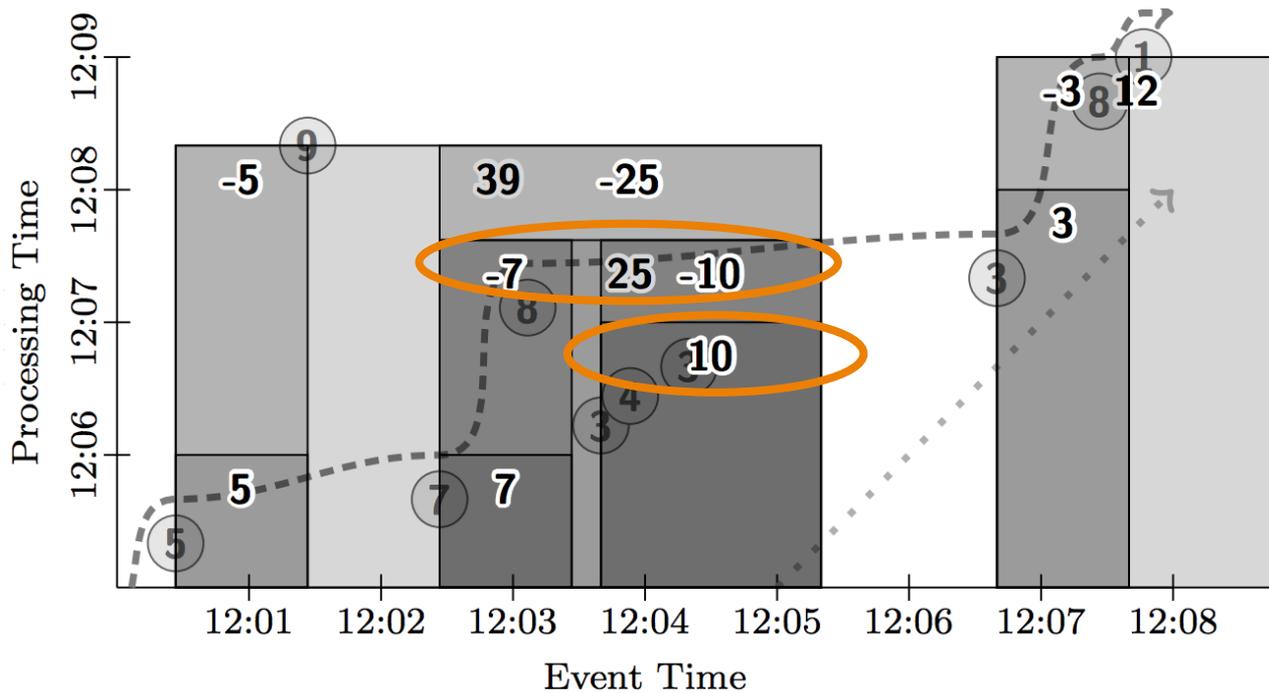
```
PCollection<KV<String, Integer>> output = input  
    .apply(Window.into(FixedWindows.of(2, MINUTES))  
        .trigger(Repeat(AtWatermark()))  
        .accumulating())
```

Option to  
repeat at  
processing  
time  
intervals



# SESSIONS, RETRACTING

```
output = input.apply(  
Window.into(Sessions.gap(1,Min))  
.trigger(SequenceOf(  
  RepeatUntil(  
    AtPeriod(1, MINUTE),  
    AtWatermark()),  
  Repeat(AtWatermark())))  
.accumulatingAndRetracting(  
.apply(Sum.integersPerKey())
```



# LESSONS / EXPERIENCES

- Don't rely on completeness
- Be flexible, diverse use cases
  - Billing
  - Recommendation
  - Anomaly detection
- Support analysis in context of events

# SUMMARY

- Model of streaming window triggers, processing
- Separate user-level view from implementation
- Motivated by real-world use cases, Cloud Dataflow SDK