Enabling real-time insights through stream processing in Python

Project Repository: github.com/Point72/csp

Materials: github.com/AdamGlustein/csp-pydata-london-2024

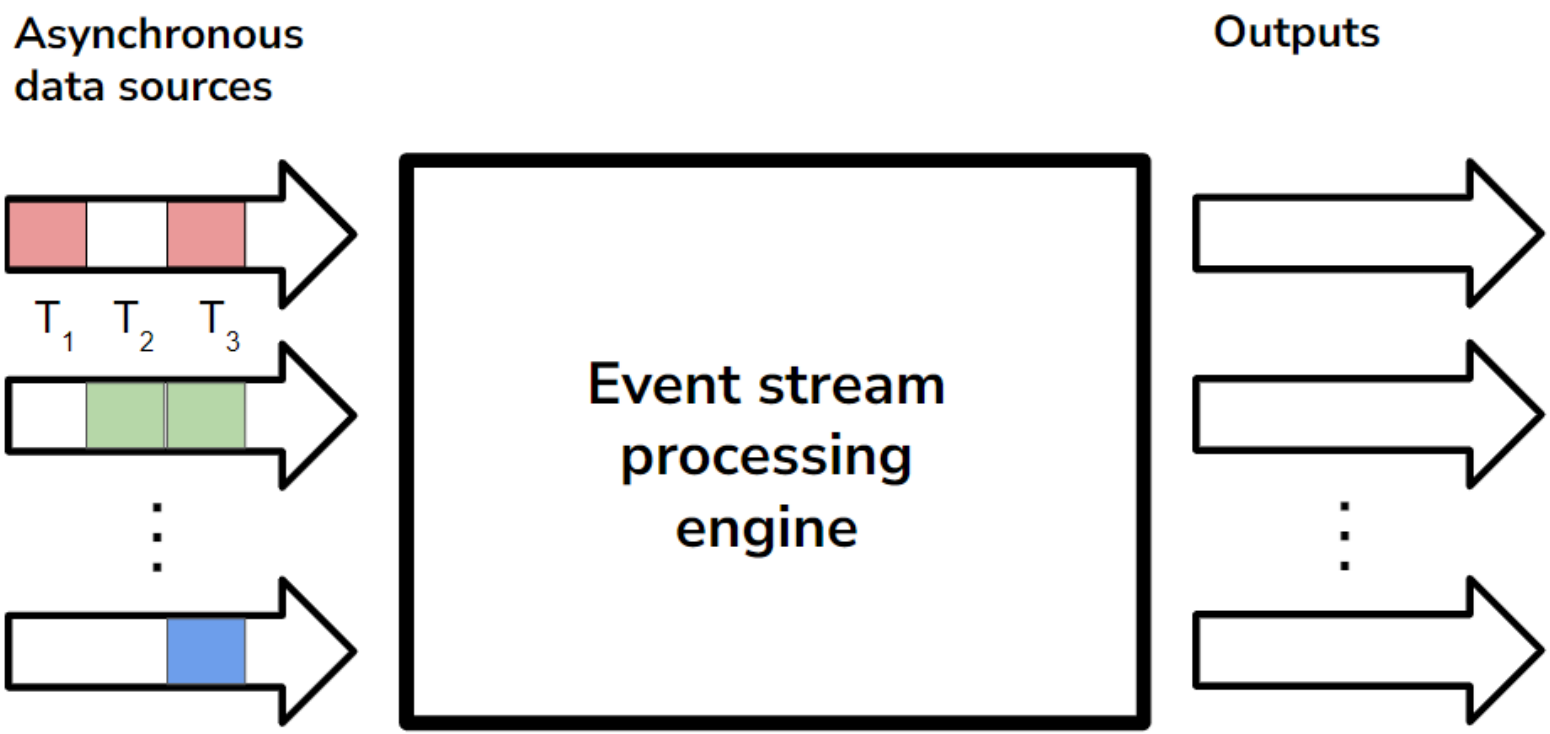
Adam Glustein

PyData London: June 15, 2024

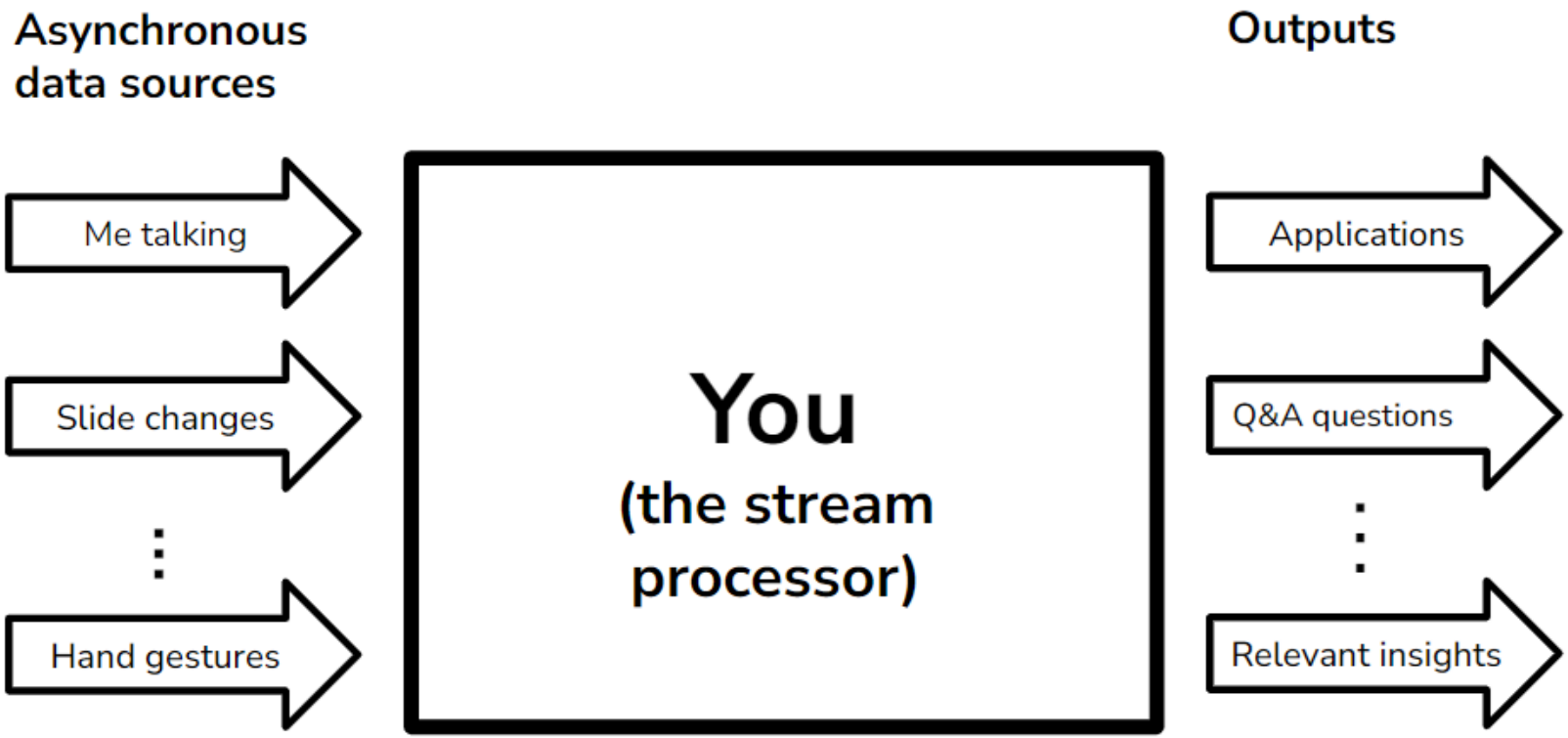
Event stream processing

- React to multiple realtime **events** that occur at unpredictable times
- Humans are naturally good at this!

Event stream processing



Event stream processing



What you will learn in this talk

- what **stream processing** is
- where stream processing can be most useful
- how to create a streaming application using **csp**

A bit about myself

- Quantitative Developer at **Point72** in New York, USA
- Contributor to `csp` since 2022

Stream processing basics

What does a good stream processor need to do?

1. **Coordinate** multiple input streams
2. **Transform** data efficiently
3. **Convert** outputs to useful data formats

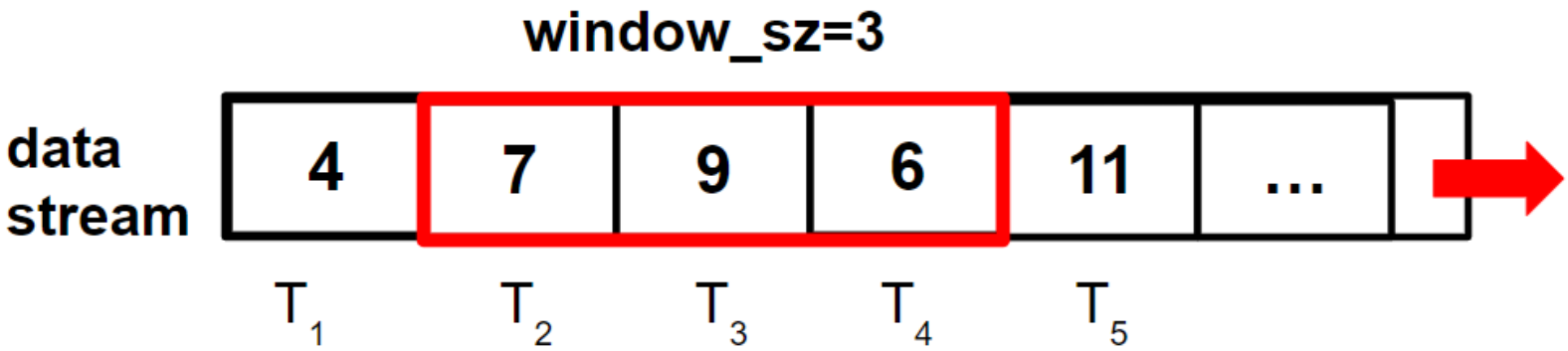
Also needs to work the same in **historical** and **real-time** modes.

Coordinate multiple input feeds

- Key challenges: order and synchronization
- Real-time sources: **Kafka**, web endpoints...
- Historical sources: **Parquet**, **polars**...

Transform data efficiently

- Aggregations, filtering, sampling
- **Rolling window** statistics (i.e moving averages)



- Bespoke logic (i.e. calling a pre-trained model)

Convert to useful output

- Same idea as ingesting useful input
- Output can be **predictive**

Current stream processing ecosystem

bytewax

- Efficient Rust implementation
- Wide support for data formats (*connectors*)

Current stream processing ecosystem

Flink

- Stateful, fault-tolerant
- *Watermarks*: complex but highly flexible

Current stream processing ecosystem

beam

- Great for highly parallel tasks
- Multi-language support (Python, Java, Go, etc.)

Current stream processing ecosystem

Pure Python and still widely used

Can be used for simple pipelines or integrated with another framework

How CSP fits in

Strengths

- Easy to get started
- No infrastructure constraints
- Seamless historical to real-time transition
- Efficient C++ runtime

Current Limitations

- No parallel execution
- Python API only

Brief walk-through of CSP

I said stream processors need to do three things:

- **Coordinate** input data streams - input adapters
- **Transform** data - csp nodes
- **Convert** to useful output - output adapters

Put these together and you have a **csp graph**

Hello World in CSP

```
1 @csp.graph
2 def hello_world():
3   hw = csp.const("hElLo wOrLd") # input adapter
4   low = csp.apply(hw, lambda x: x.title(), str) # node
5   csp.print("Message", low) # output adapter
6
7 csp.show_graph(hello_world)
```

Hello World in CSP

```
from datetime import datetime, timedelta

csp.run(hello_world, starttime=datetime.utcnow(),
    endtime=timedelta(seconds=1), realtime=True)
```

Output

```
2024-05-27 13:10:33.160102 Message:Hello World
```

We can also run in the past

- CSP keeps its own internal *engine time*
- Seamless transition to playback mode

```
1 csp.run(hello_world, starttime=datetime(2022,1,1),
2     endtime=timedelta(seconds=1), realtime=False)
```

Output

```
1 2022-01-01 00:00:00 Message:Hello World
```

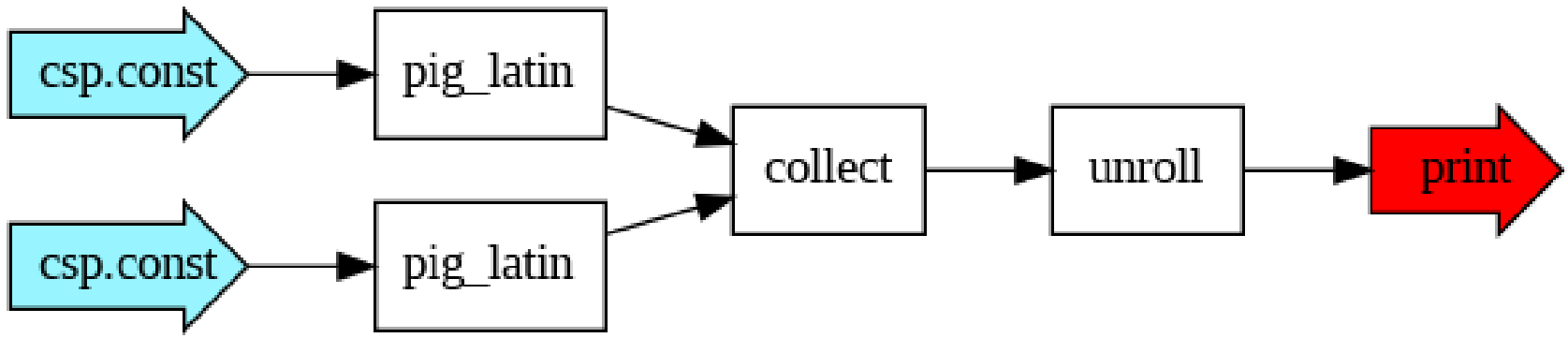
Writing your own CSP nodes

- Nodes transform **time series** data

```
from csp import ts

@csp.node
def pig_latin(text: ts[str]) -> ts[str]:
  is_vowel = lambda c : c in "aeiou"
  assert len(text) > 2
  if not is_vowel(text[0]):
    if is_vowel(text[1]):
      pl = text[1:]+text[0]
    else:
      pl = text[2:]+text[:2]
  else:
    pl = text+"w"

  return pl+"ay"
```

Writing your own CSP nodes

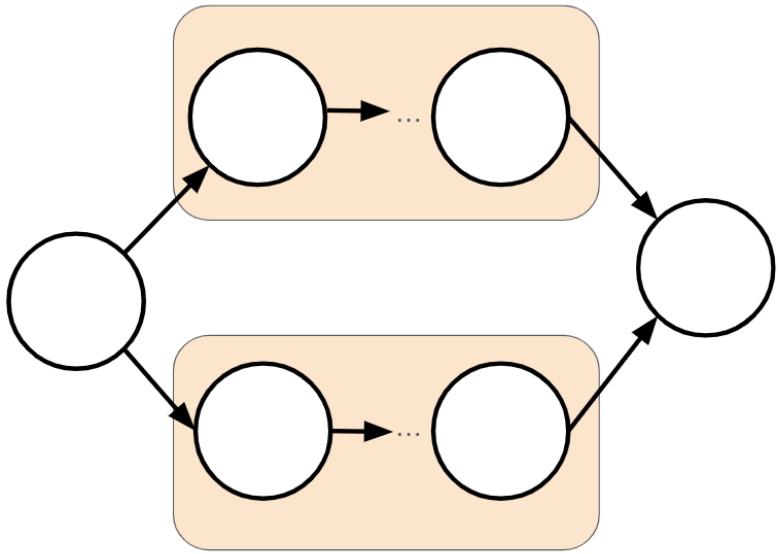
```
@csp.graph
def ellohay_orldway():
  hello = csp.const("hello")
  world = csp.const("world")
  latin = [pig_latin(hello), pig_latin(world)]
  csp.print("Pig Latin", csp.flatten(latin))

csp.show_graph(ellohay_orldway)
```



Nodes and graphs

- Nodes are **atomic** units of computation
- Graphs are collections of nodes

```
1 @csp.graph
2 def subgraph(x: ts[T]):
3     ...
4
5 @csp.graph
6 def main_graph():
7   for source in
      data_sources:
8     subgraph(source)
9     ...
```



Nodes and graphs

Nodes can maintain a per-instance **state** and schedule internal events

```
@csp.node
def poisson_counter(lam: float) -> ts[int]:
  with csp.alarms(): # An internal time-series
    a = csp.alarm(int)
  with csp.state(): # State stored per node instance
    s_cnt = 0
  with csp.start(): # Block runs once at graph start
    delay = np.random.exponential(lam)
    csp.schedule_alarm(a, timedelta(seconds=delay), 1)

  if csp.ticked(a):
    s_cnt += 1
    new_delay = np.random.exponential(lam)
    csp.schedule_alarm(a,
        timedelta(seconds=new_delay), 1)
    return s_cnt
```

Stream processing use cases

- Historical replay is key for research/testing
- Real deployment uses **live** data
  - Financial markets
  - Transportation networks
  - Climate analysis
  - Many more!

A dashboard for transit methods in New York City

- Real-time feeds available:
  - Bus and commuter rail alerts (from the MTA)
  - Bike share station status (from CitiBike)
  - Subway train positions/delays (from the MTA)
- These are **asynchronous, real-time** data sources

Summary

- Stream processing is a powerful technique for gaining insights from **live** data
- Common problem: moving from historical to real-time execution
- **Composable stream processing** (csp) allows for a seamless transition