

# Simplify stream processing

with Python, Quix, and InfluxDB

### Hello, nice to meet you! 🁋



Tomas Neubauer CTO & Co-founder, Quix

Previously McLaren technical lead

# Racing background

Roots in real-time data processing in the most extreme, time-critical environment.

- 50,000 channels per car
- 1.5 kHz per channel
- 1,000s realtime models and simulations

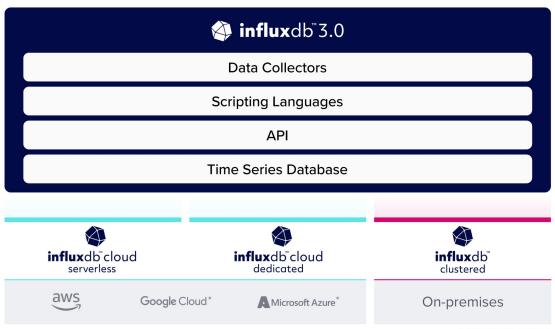




#### What is InfluxDB?

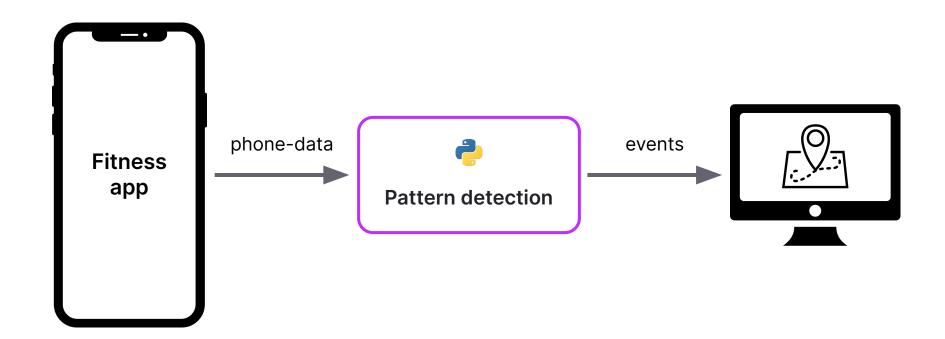
#### InfluxDB. It's About Time.

Manage all types of time series data in a single, purpose-built database. Run at any scale in any environment in the cloud, on-premises, or at the edge.



\* Availability to be announced

#### Live demo!



## Kafka

## Streaming

# Python

### ML Deployment

**REST API vs Streaming** 

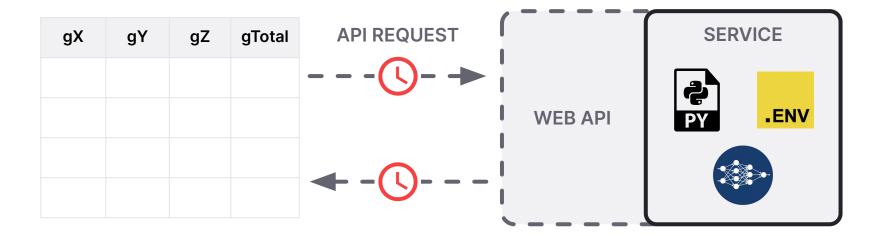
#### ML Deployment with API



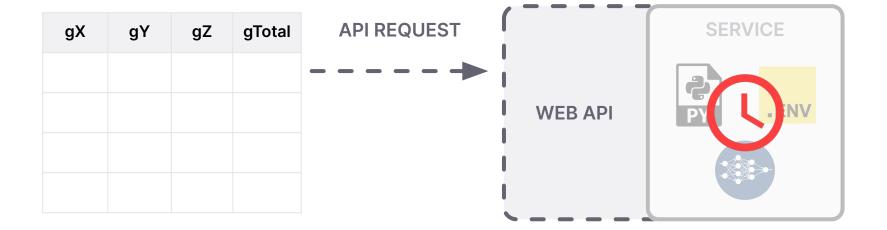
gX	gY	gZ	gTotal	Crash
0.5	0.3	0.1	0.9	1

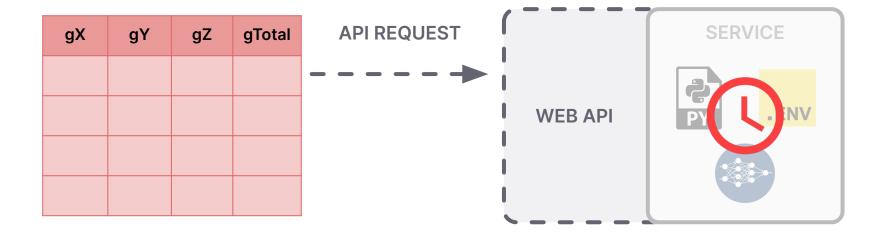
### Issues with REST APIs

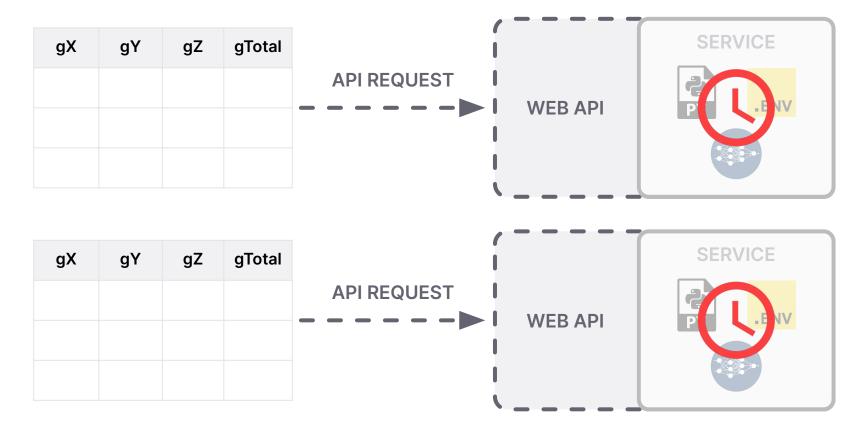
**REST API vs Streaming** 



- CPU overhead
- Introducing delay
- Requests gets lost in case of service downtime or slow performance



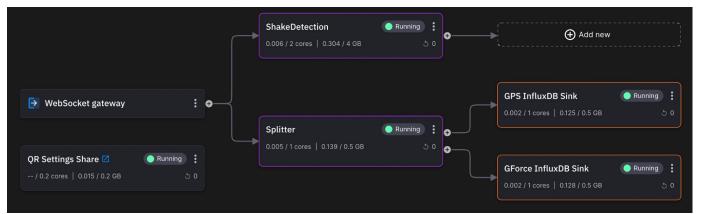




# Event streaming applications

#### What is an event streaming application?

- Built with Kafka & microservices
- Processes and transports data as continuous streams of events
  - Sensor data
  - Mouse clicks
  - Financial data
- Contains a pipelines to ingest  $\rightarrow$  process  $\rightarrow$  sink data



# How to build event streaming apps

#### Event streaming architecture

When you build **event streaming applications** with **Kafka**, there are two options:

- 1. Just build an application with microservices uses the Kafka **producer** and **consumer** APIs directly
  - combine Kubernetes with Kafka
- 2. Adopt a full-fledged stream processing framework (Flink, Spark streaming, Beam etc.)
  - combine microservices in Kubernetes, Flink cluster, Flink jobs and Kafka

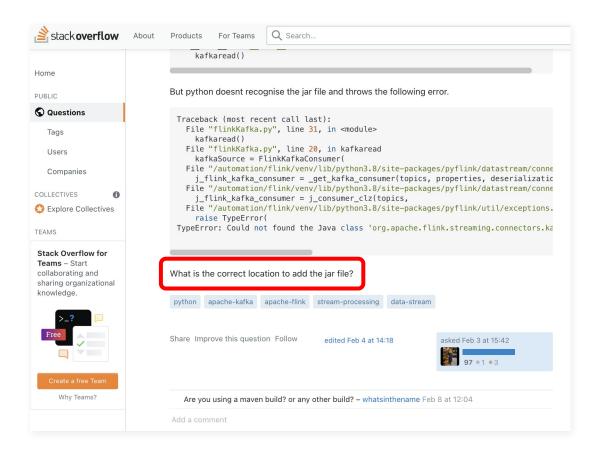
#### Kafka producer and consumer APIs

- Works for simple stuff like one-message-at-a-time processing
- No external dependencies like JVM
- Gets very complicated when stateful processing is needed like calculation aggregations or joining multiple streams
- CI/CD overhead
  - Manage your own Kubernetes
  - Own **build** and **release** pipelines
  - Build own monitoring and observability

#### Stream processing frameworks

- Fully fledged stream processing frameworks solves stateful, more complex operations
- You get CI/CD and observability out of box for your data pipelines
  - but not application microservices
- Increased complexity in many dimensions:
  - Java dependency
  - Deployment gets difficult because code is not running on its own but in server side cluster (Flink cluster or Spark cluster)
  - Debugging is difficult
  - Performance optimization is difficult

#### JAR files...



#### Connecting Flink to Kafka is difficult

```
CREATE TABLE country target (
country VARCHAR,
avg age BIGINT,
nr_people BIGINT,
PRIMARY KEY (country) NOT ENFORCED
) WITH (
  'connector' = 'upsert-kafka',
  'property-version' = 'universal',
  'properties.bootstrap.servers' = '<host>:<port>',
  'topic' = 'country agg'.
  'value.format' = 'json',
  'key.format' = 'json',
  'properties.security.protocol' = 'SSL',
  'properties.ssl.endpoint.identification.algorithm' = '',
  'properties.ssl.truststore.location' = '/settings/certs/client.truststore.jks',
  'properties.ssl.truststore.password' = 'password123',
  'properties.ssl.keystore.type' = 'PKCS12',
  'properties.ssl.keystore.location' = '/settings/certs/client.keystore.p12',
  'properties.ssl.keystore.password' = 'password123',
  'properties.ssl.key.password' = 'password123',
  'properties.group.id' = 'my-working-group'
);
```

#### SQL looks easy to use but...

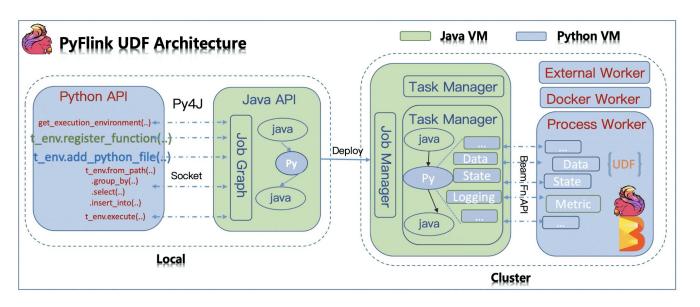
```
select * from country_target;
```

We should see something like this:

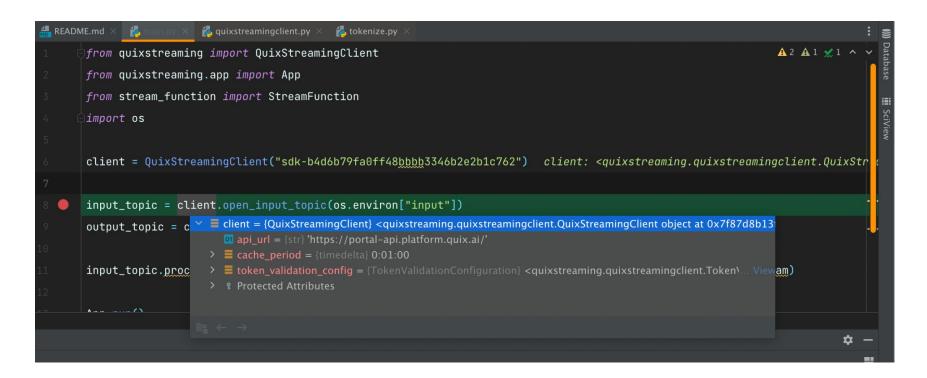
+/-	country	avg_age	nr_people
+	USA	40	1
+	England	35	1
+	Italy	25	1
_	Italy	25	1
+	Italy	35	2

#### **UDFs** are nasty

- Poor development experience
  - Logs only accessible from server, no debugging possible
- Performance hit caused by interface between JVM and Python



### DEBUGGING!!!



#### Building your own architecture is costly

Lower

8 months 3 Months 3 Weeks 7 Days **Build infrastructure** Develop Release Observe Effort to build Complex Effectively the first app testing monitoring and Technical complexities debugging Data Orchestration Design complexities consistency and and management synchronisation Platform team: 11 FTE Engineering: 2 FTE + Data team: 2 FTE

Cost & Risk

Higher



# One tool to build event streaming apps

#### Accelerated application development



Weeks

Hours - - - - -

Minutes -

#### Develop

Use free open-source connectors & code samples to develop faster. Use Python to process streams and get ML predictions.

#### Release

laC: code, test and deploy event streaming applications with a single source of truth powered by Kafka, Docker and Git.

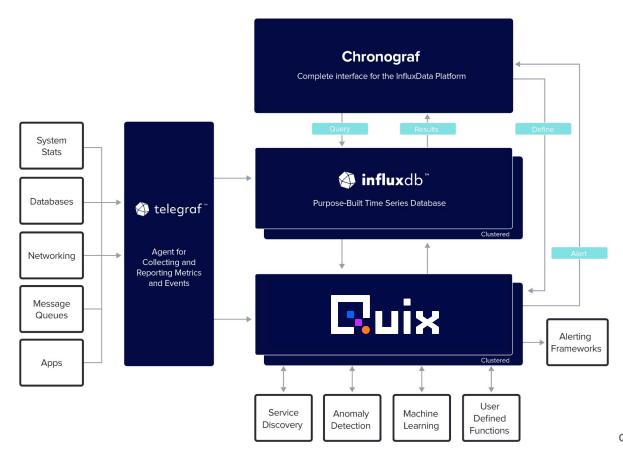
#### Observe

A suite of observability tools designed to give you in-depth insights into your event-driven architecture.

Engineering: 2 FTE + Data team: 2 FTE

**Predictable Cost & Risk** 

#### Easily integrate with InfluxDB Cloud?



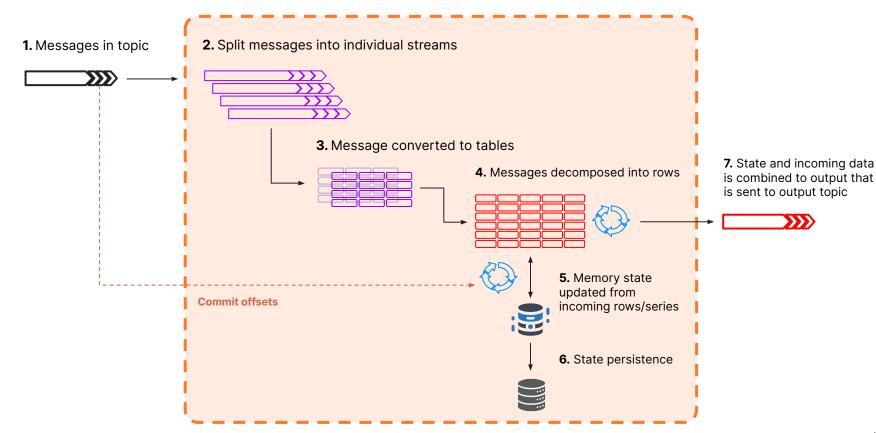
#### A new way to process streaming data

- Application development environment managing CI/CD and releases for data pipelines, Kafka and microservices in one tool
- Combining Kafka API approach with a **Python stream processing library**
- **Standalone library** that runs:
  - Locally for development and debugging
  - In docker or in Kubernetes for production deployments at scale
- **Seamless integration** with external systems like **InfluxDB Cloud**

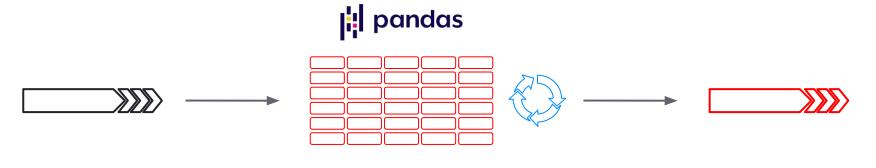
## Quix Streams

**Python Streaming DataFrames** 

#### Stateful processing with Pub & Sub client libraries



#### **Quix Streams PySDF**



1. Messages in topic

2. Messages decomposed as rows available via pandas API **3.** Messages processed through pipeline defined as pandas operations. Output streamed to output topic.

- Automatic state management
- Automatic checkpointing
- Automatic message serialization/deserialization

#### Quix Streams PySDF API

```
# Define topics with serialization settings
input_topic = Topic("input_topic", value_deserializer=JSONDeserializer())
output_topic = Topic("output_topic", value_serializer=JSONSerializer())
# Define a StreamingDataframe to transform the data
sdf = StreamingDataFrame(topics=[input_topic])
# Select only "field_A", "field_B", "field_C" from the incoming message
sdf = sdf[['field_A', 'field_B', 'field_C']]
# Filter only messages with "field_A" > 5 and "field_B" < 4
sdf = sdf[(sdf['field_A'] > 5) & (sdf['field_B'] < 4)]</pre>
# Produce the result to the output topic
sdf = sdf.to topic(output topic)
# Run the dataframe
with Runner(broker_address="localhost:9092", consumer_group="test", auto_offset_r
    runner run(sdf)
```

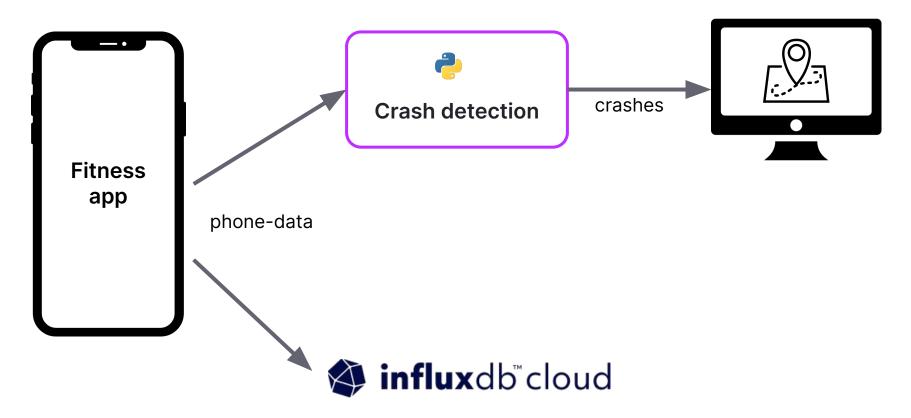
## Quix Streams PySDF V1.0 features

```
# Define topics with JSON deserialization
input_topic = Topic("input_topic", value_deserializer=JSONDeserializer())
# Define a StreamingDataframe
sdf = StreamingDataFrame(topics=[input topic])
# Calculate sum of values in "A" over the tumbling window of size 10s
a total 10s = sdf['A'].rolling(period=10, window type='tumbling').sum()
# Update the current message with the result of window aggregation
sdf['A total 10s'] = a total 10s.value()
# Set additional window metadata
sdf['A_total_10s__start'] = a_total_10s.window_start()
sdf['A total 10s end'] = a total 10s.window end()
```

# Demo

See it in action!

## Use case 1: Real-time event detection app



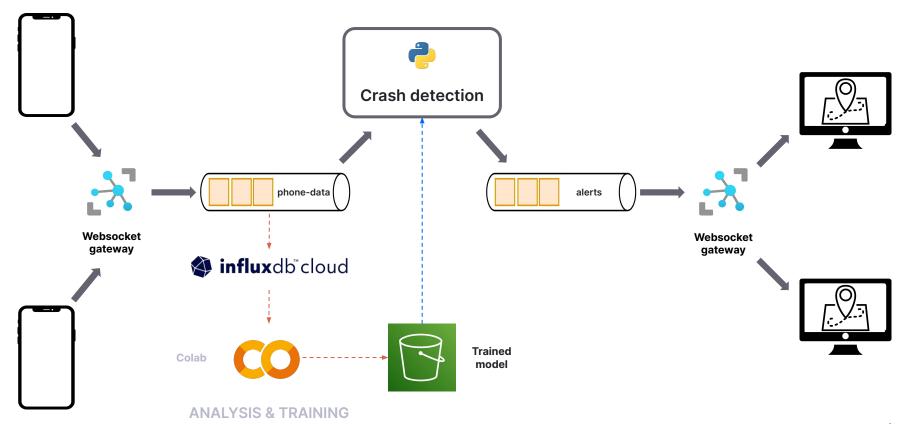
# Use case 2: Training real-time ML models with InfluxDB



# Use case 2: Training real-time ML models with InfluxDB



# Complete event streaming application architecture



# How it works

Kafka + Kubernetes + Python

# Our approach to stream processing



#### **Containers**

Containers running in Kubernetes scaling hand to hand with Kafka for compute scalability.



#### Kafka

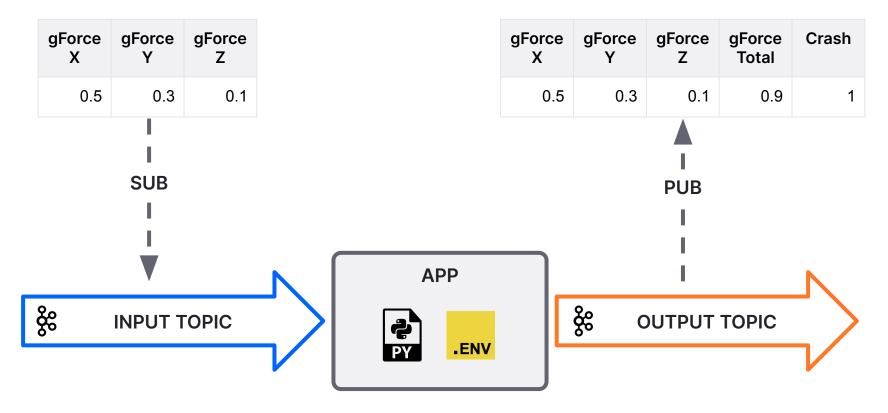
Handle your data reliably and efficiently in memory with Kafka. Using Kafka partitions, replica system and persistence to deliver scalability and robustness.



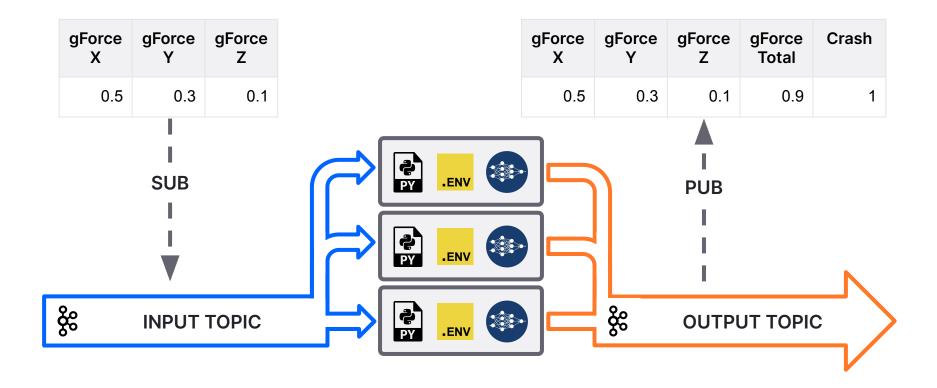
#### **Python**

Python gives you flexibility. It lets you transform data, not just query it. From simple filtering to ML use cases like video processing.

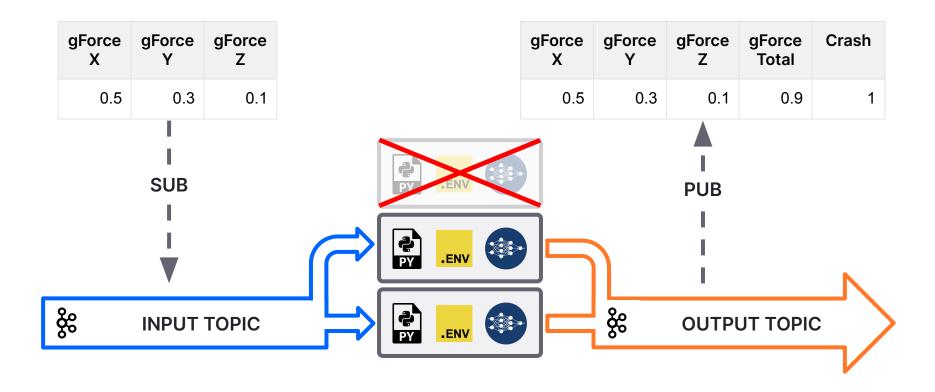
# Processing with streaming



### Scale



### Fault tolerant



# Try Quix



Sign up



# Thank you



info@quix.io | www.quix.io

#### InfluxDB Platform

Database & platform for handling time series data at massive scale

