



Fast-Track Machine Learning Operationalization Through Streaming Integration

May 2018

Speakers and Agenda



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- Background
- Introduction To Striim
- Lab : Network Intrusion Detection System
- Q&A

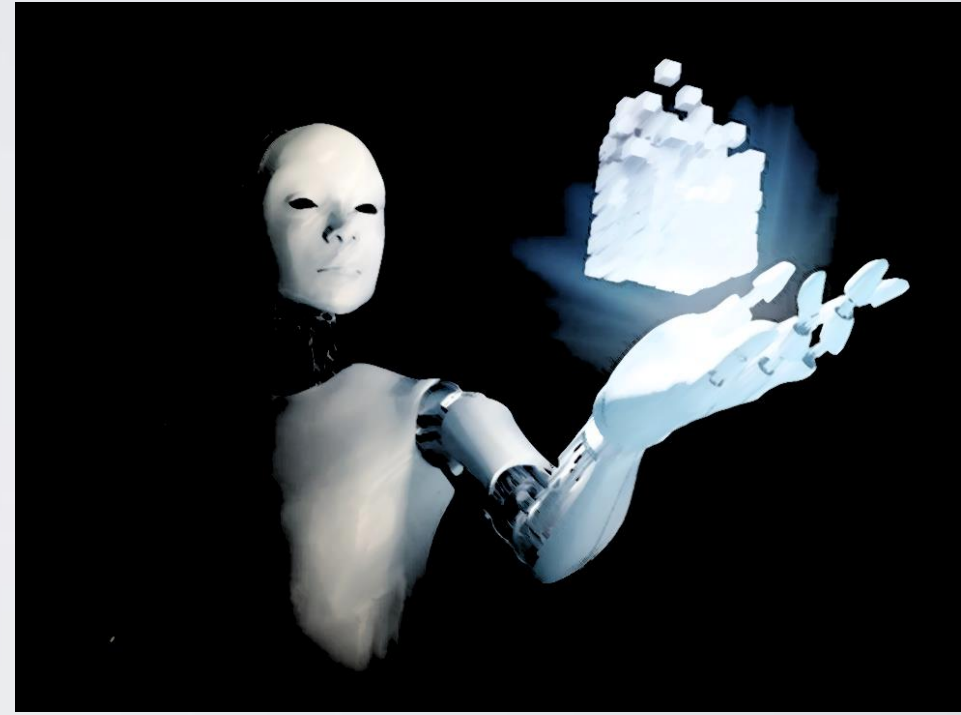
Operational Machine Learning Facts

The value of ML is based on the real-time handling of high data volume, velocity, and variety at scale

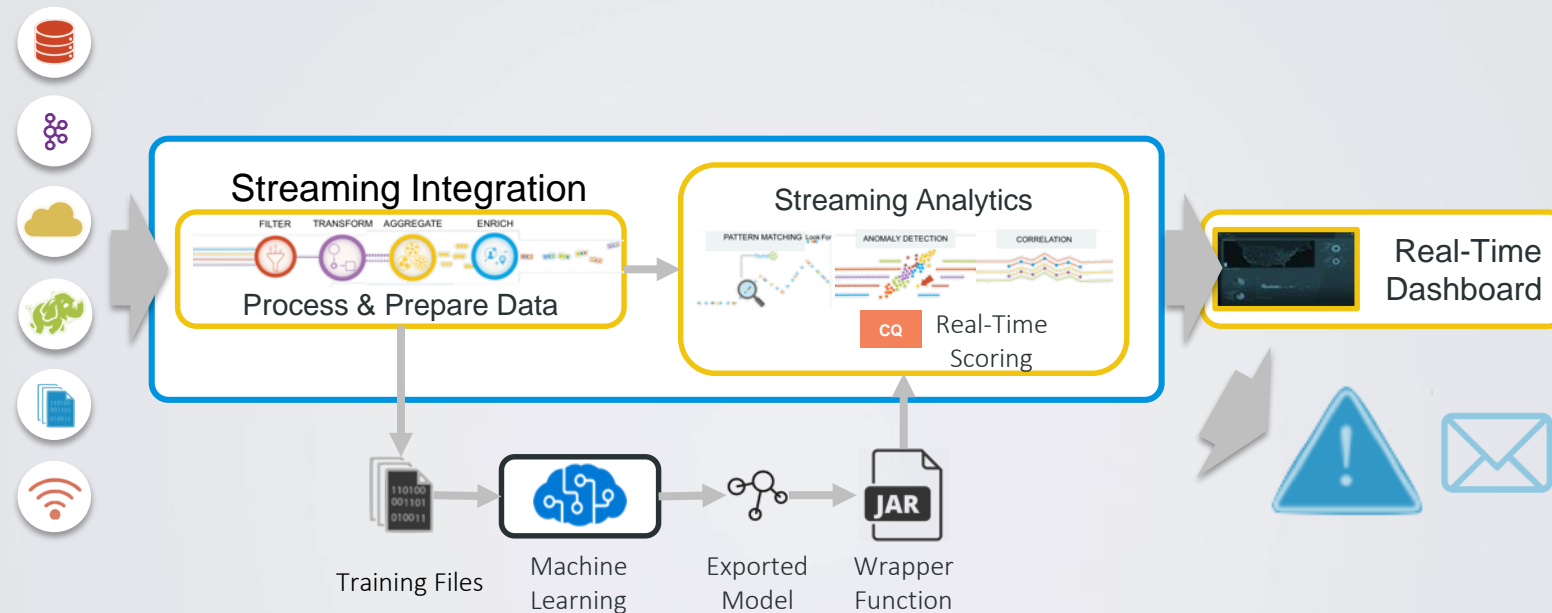
Intensive real-time pre-processing and feature extraction is required before feeding raw data into models

Static models cannot fit dynamic data in operational systems even they are fine-tuned offline

Operational systems demand continuous insights from model serving and minimal human intervention

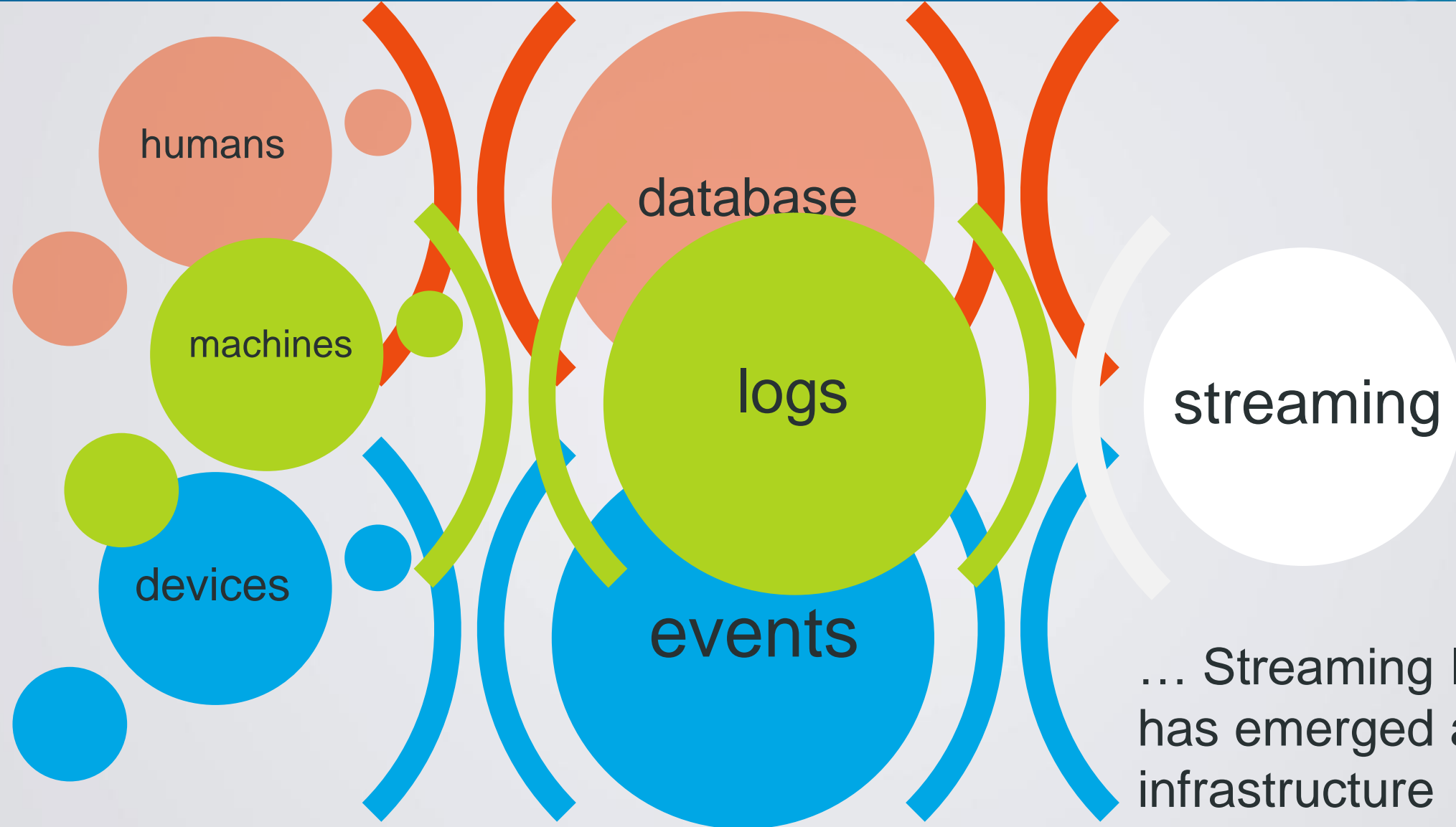


Striim Solution of Fast-Track ML Operationalization



- Filter, enrich and otherwise prepare streaming data
- Land data continuously, in an appropriate format for training a machine learning model
- Handle model lifecycles, enabling retraining if the model no longer fits the data
- Integrate a trained model into the real-time data stream to make continuous predictions
- Visualize the real-time data and associated predictions, and alert on issues

Data Arrives in Streams - Not in Batches



... Streaming Integration
has emerged as a major
infrastructure
requirement

Striim Is Built For Streaming Integration

It's all about
continuously moving
any enterprise data,
while:



Handling extreme volumes of data
at scale with high throughput








Processing, analyzing, and
correlating data in flight



Making data valuable, verifiable,
and visible in real time

Why Are Companies Using Streaming Integration?

	Data Distribution and Consistency	<ul style="list-style-type: none">• Kafka Integration and Processing• RDMS Integration• Data Grid Cache Consistency
	Cloud Adoption	<ul style="list-style-type: none">• Zero Downtime Migration to Cloud• Continuous Real-Time Data Integration
	Integration for Analytics	<ul style="list-style-type: none">• Hadoop Integration• Operational DS/DW Integration• Offloading Reporting
	Real-Time Analytics	<ul style="list-style-type: none">• Next-Generation Analytics• Real-Time Alerts• Data Visualization
	Internet of Things	<ul style="list-style-type: none">• IoT Edge Processing and Analytics

Customers Are Modernizing

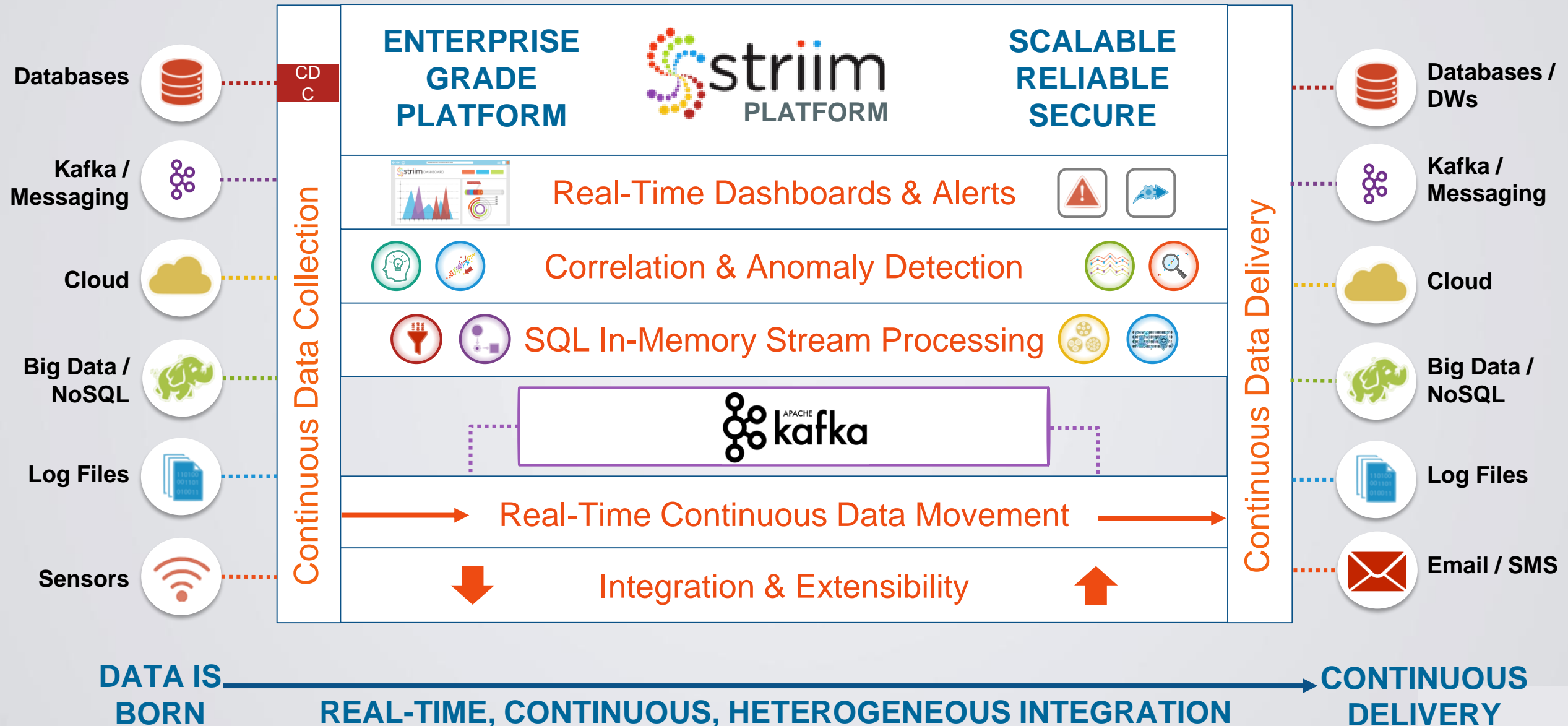
Moving to a “streaming first” data architecture, supporting cloud, streaming analytics, and IoT.

Bridge the old and new worlds of data.

Streaming Integration is the foundation for data modernization initiatives.



Striim Platform for Streaming Integration with Intelligence



Streaming Integration with Intelligence

CONTINUOUS DATA INGESTION

Parsers

Delimited
JSON
XML
Free Text
Binary
Name/Value
Zipped
AVRO
GoldenGate
Apache Log
Sys Log
MS Event Log
Mail Log
SNMP
CollectD
CEF
DHCP Log
WCF
+Others

DBs



Oracle CDC
MS SQL CDC
MySQL CDC
HPE NSK CDC
Maria DB CDC
JDBC/SQL

Cloud



Amazon S3
AWS RDS
Salesforce

Files



Log Files
System Files
Batch Files

Network



TCP
UDP
HTTP
MQTT
Netflow
PCAP
OPC-UA

Messaging



Kafka
Flume
JMS
AMQP

Big Data



HDFS
HBase
Hive



DRAG & DROP UI

STREAM PROCESSING WITH INTELLIGENCE



REAL-TIME VISUALIZATION

CONTINUOUS DATA DELIVERY

DBs/DWs



Oracle
MS SQL
MySQL
Teradata
PostgreSQL
MemSQL
JDBC/SQL

Files



Network



Messaging



Big Data



Cloud



Alerting



MQTT
OPC-UA

Kafka
JMS
AMQP

HDFS
HBase
Hive
Hazelcast

Azure Blob
Azure SQL DB
Azure HDInsight
Amazon S3
Amazon Redshift
Amazon Kinesis
Google Big Query

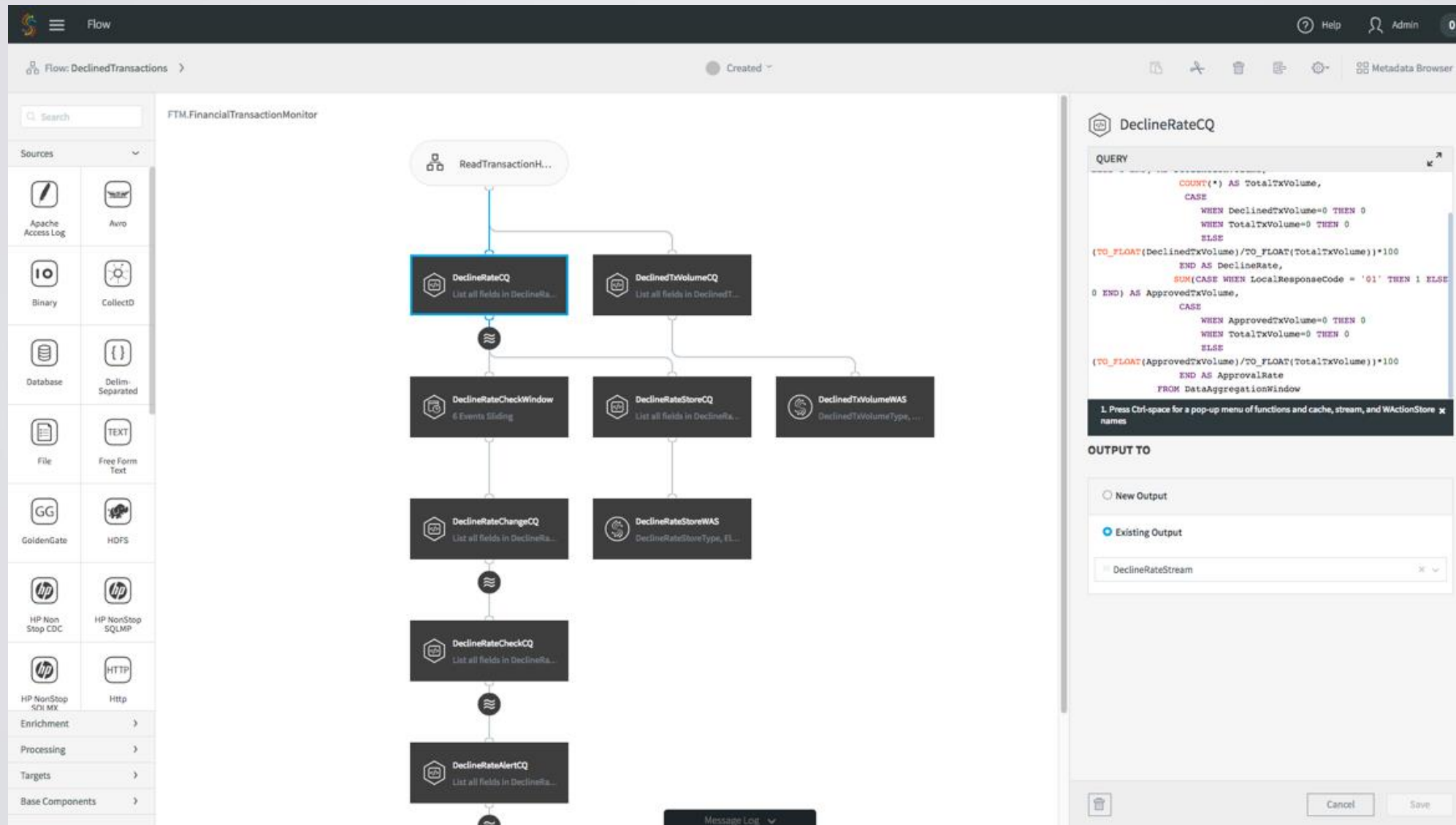
Email
SMS

Formats

Delimited
JSON
XML
AVRO
Template



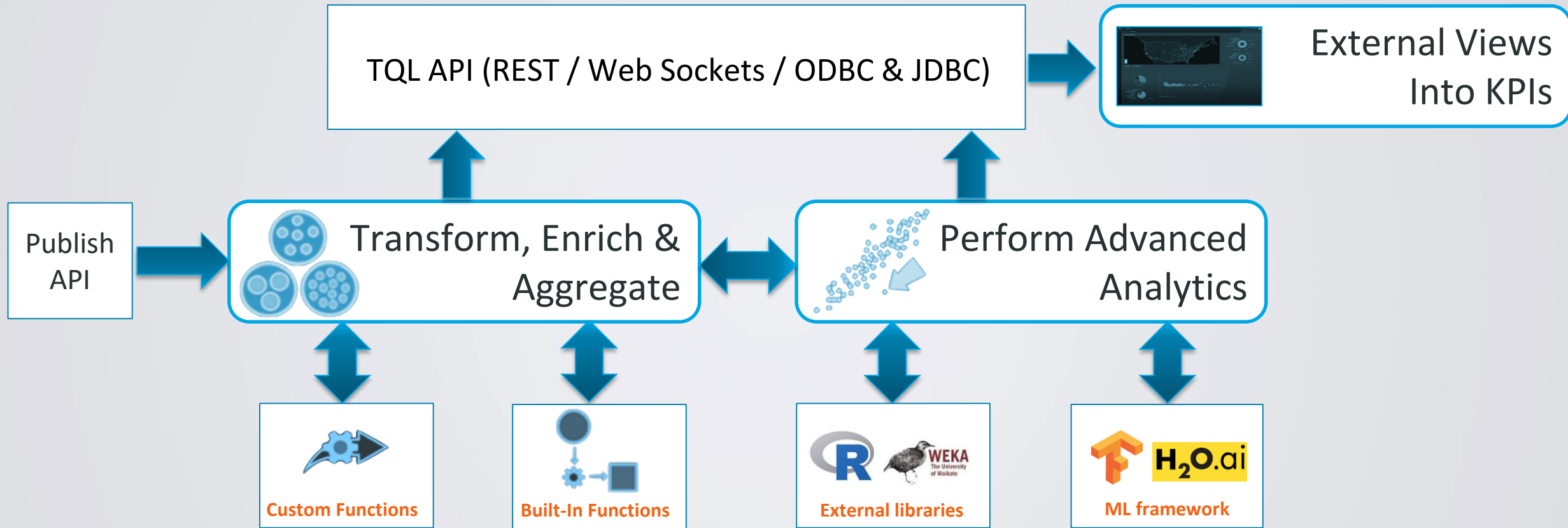
Integration and Analytics Through Data Flows



Visualization Through Streaming Dashboards



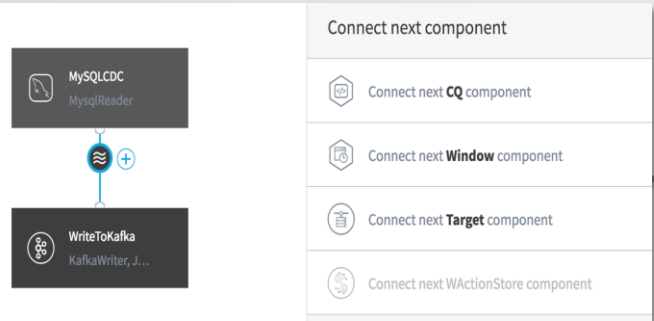
Striim – Integration Overview



Enterprise Grade
Clustered, Distributed, Scalable, Reliable and Secure

Striim Application

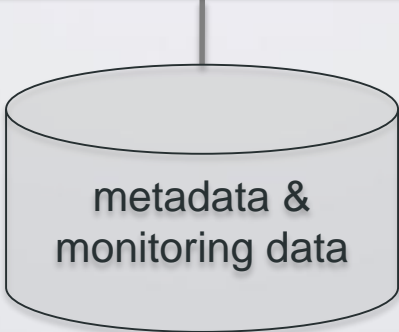
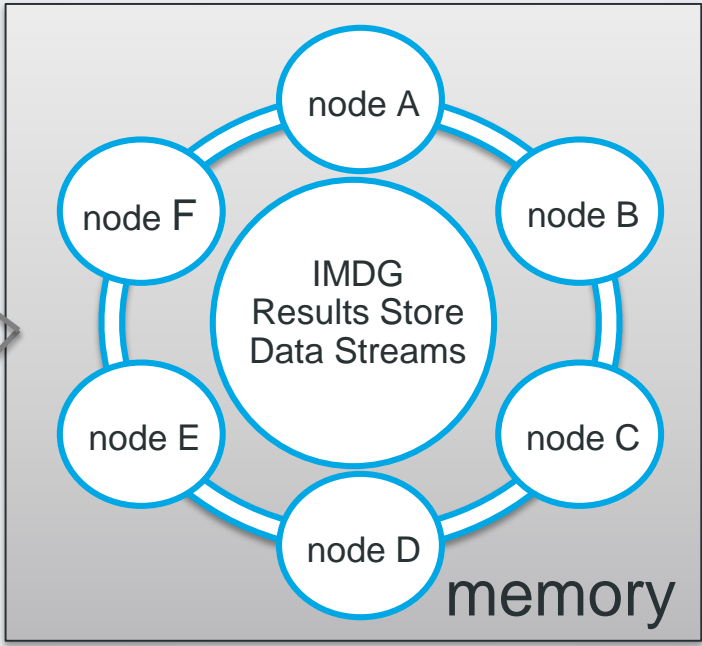
Flow Designer UI



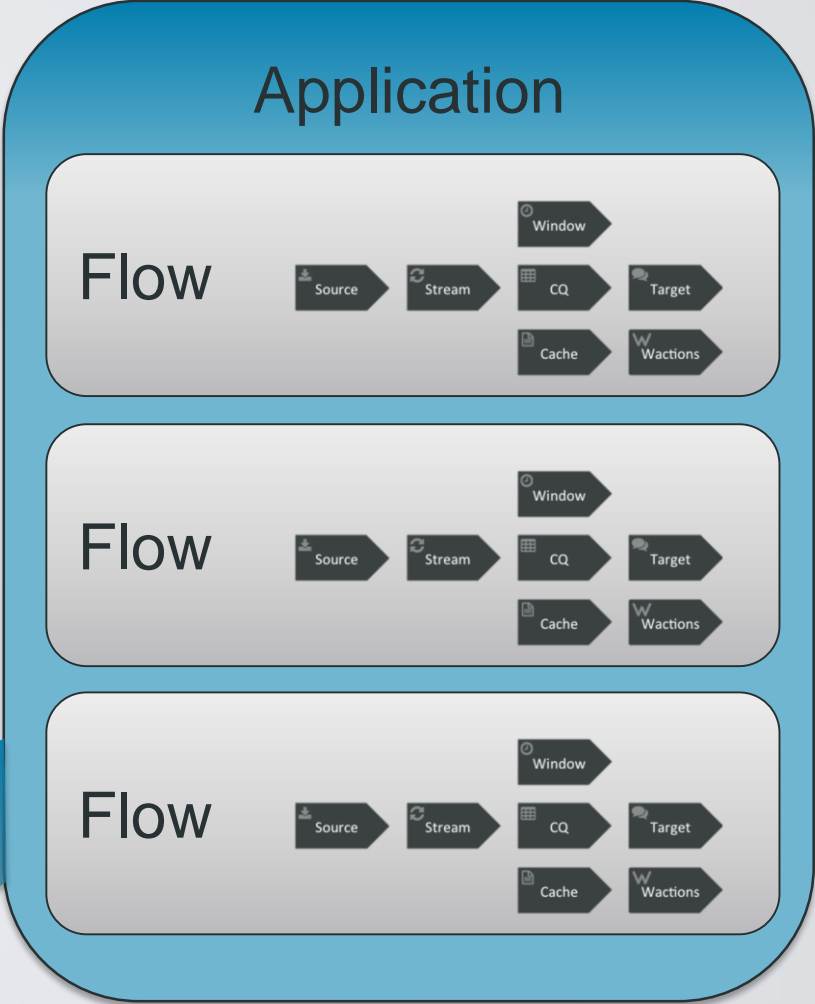
Tungsten console

```
CREATE APPLICATION MultiLogApp;  
CREATE FLOW MonitorLogs;  
CREATE SOURCE AccessLogSource USING...  
CREATE TYPE AccessLogEntry ...  
CREATE STREAM AccessStream OF...  
CREATE CQ ParseAccessLog ...  
W >
```

Striim cluster



Application



Core Striim Components



Source

Source accesses external data and provides real-time continuous events into streams



Stream

Stream carries data between components and nodes



Type

Type is a named set of fields, each has a name and a data type, such as *Integer* or *String*



Window

Window provides moving snapshot/collection of events for aggregates and models



Cache

Cache is external contextual data made available using distributed in-memory grid



CQ

A Continuous Query emits big data records after processing real-time streaming events (can process data from streams, windows, caches, event tables, and stores)



Target

Target outputs real-time big data records to external systems

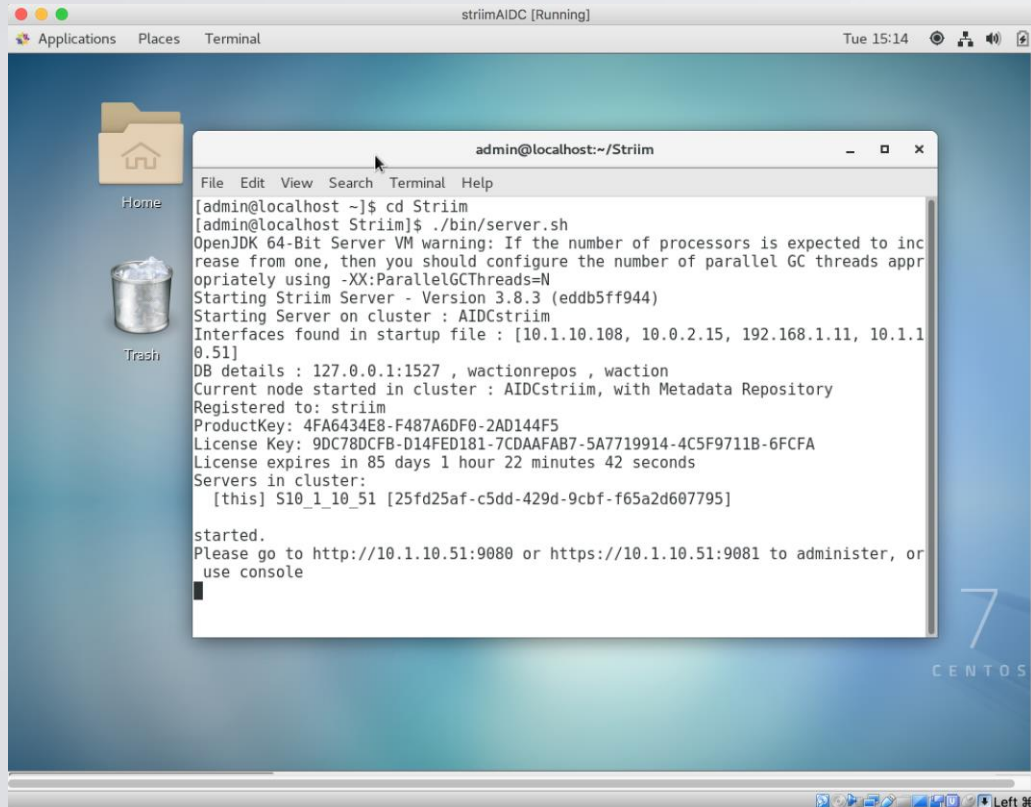


Results

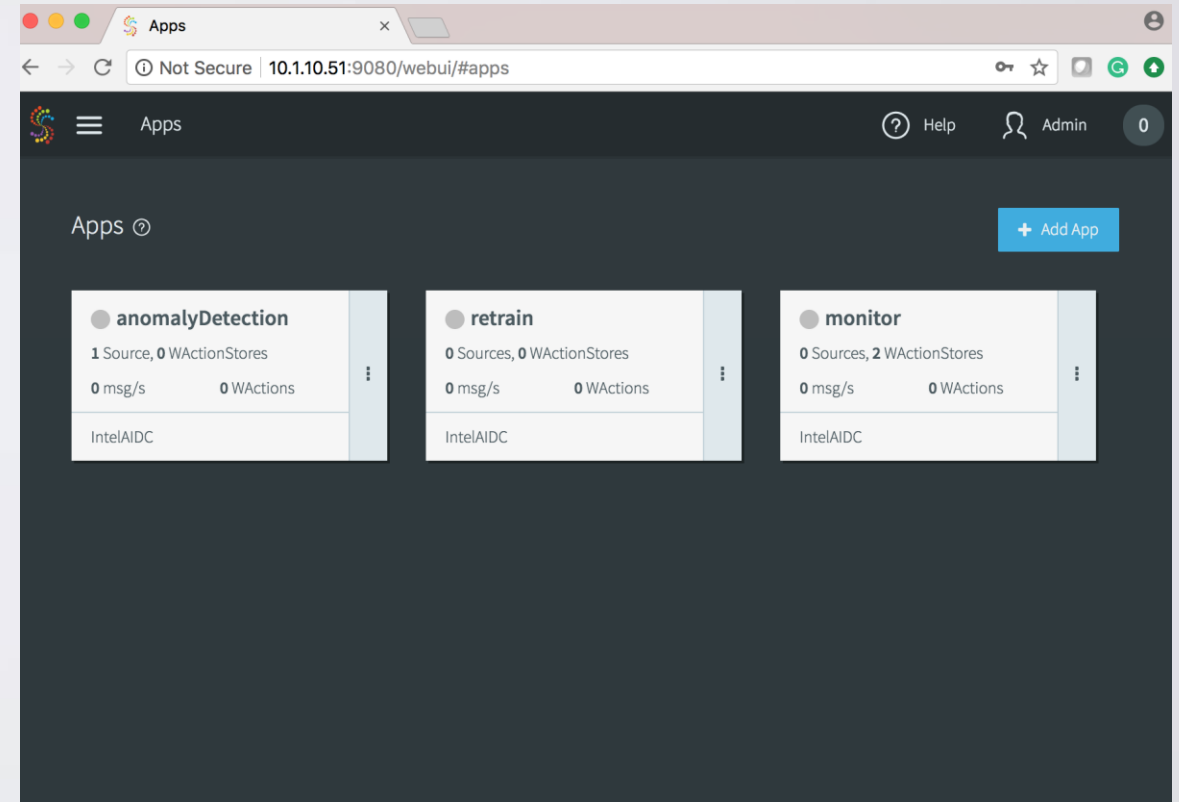
A Results Store contains results of processing within the Striim server, defines the data allowed in the store and how it is persisted to a backend system (default ES)

Lab: Network Intrusion Detection System (NIDS)

Start Striim server in virtual machine striimAIDC



Navigate to Striim Web UI in your host/VM browser



Note: if the URL is not accessible from you host browser, go to *Applications -> Sundry -> Firewall -> Options -> Change default zone to trusted*.

Network Intrusion Detection System (NIDS)

- Data:
 - Network flows with robust features from tcpdump analyzer
- Tasks:
 - Detect abnormal flows with low false positive rate
 - Automatically adapt model serving to data evolution
 - Continuously monitor system and alert on issues in real time
- Algorithms
 - One-Class SVM (Weka LibSVM)
 - Time series spike detection

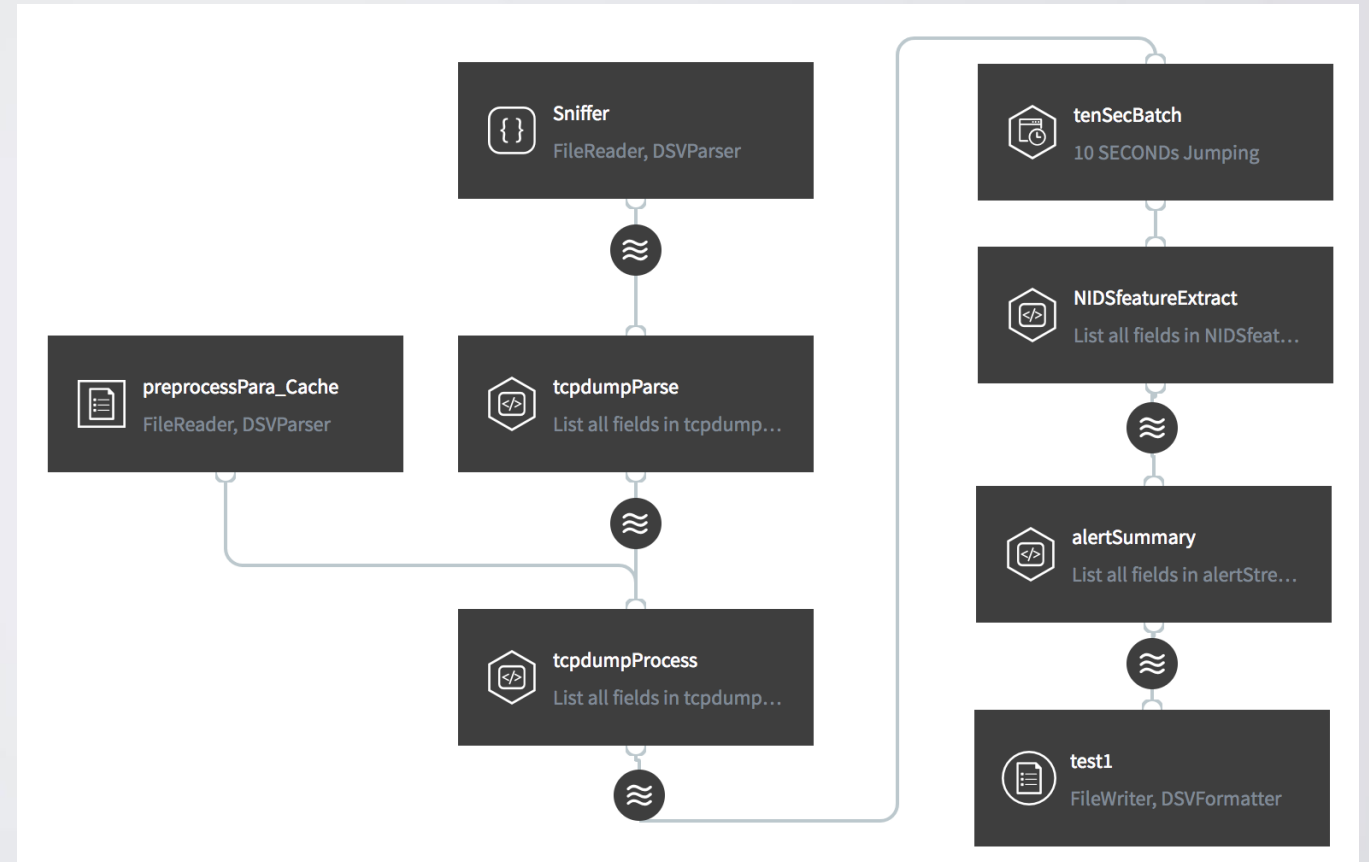
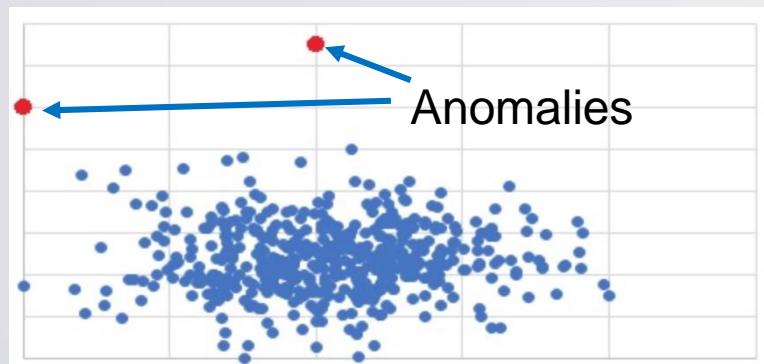
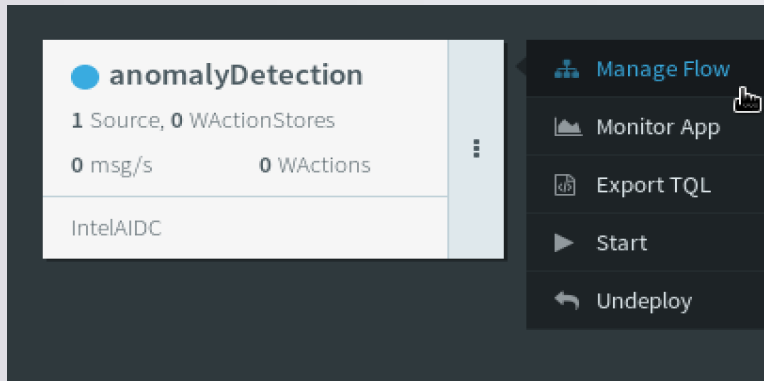
NIDS Data

Name	Type	Description
srcip	nominal	Source IP address
sport	integer	Source port number
dstip	nominal	Destination IP address
dsport	integer	Destination port number
proto	nominal	Transaction protocol
state	nominal	Indicates to the state and its dependent protocol
dur	Float	Record total duration
sbytes	Integer	Source to destination transaction bytes
dbytes	Integer	Destination to source transaction bytes
sttl	Integer	Source to destination time to live value
dttl	Integer	Destination to source time to live value
sloss	Integer	Source packets retransmitted or dropped
dloss	Integer	Destination packets retransmitted or dropped
service	nominal	http, ftp, smtp, ssh, dns, ftp-data ,irc
Sload	Float	Source bits per second
Dload	Float	Destination bits per second
Spkts	integer	Source to destination packet count
Dpkts	integer	Destination to source packet count
swin	integer	Source TCP window advertisement value
dwin	integer	Destination TCP window advertisement value
stcpb	integer	Source TCP base sequence number
dtcpb	integer	Destination TCP base sequence number
smeansz	integer	Mean of the packet size transmitted by the src
dmeansz	integer	Mean of the packet size transmitted by the dst
trans_depth	integer	Represents the pipelined depth into the connection
Sjit	Float	Source jitter (mSec)

Name	Type	Description
Djit	Float	Destination jitter (mSec)
res_bdy_len	integer	Actual uncompressed content size of the data transferred from the server's http service.
Sintpkt	Float	Source interpacket arrival time (mSec)
Dintpkt	Float	Destination interpacket arrival time (mSec)
tcprtt	Float	TCP connection setup round-trip time, the sum of 'synack' and 'ackdat'.
synack	Float	TCP connection setup time, the time between SYN and SYN_ACK.
ackdat	Float	TCP connection setup time, the time between SYN_ACK and ACK.
is_sm_ips_ports	Binary	If source and destination IP addresses equal and port numbers equal then, this variable takes value 1 else 0
ct_state_ttl	Integer	No. for each state according to specific range of values for source/destination time to live.
ct_flw_http_mthd	Integer	No. of flows that has methods such as Get and Post in http service.
is_ftp_login	Binary	If the ftp session is accessed by user and password then 1 else 0.
ct_ftp_cmd	integer	No of flows that has a command in ftp session.
ct_srv_src	integer	No. of connections that contain the same service and source address in 100 connections according to the last time.
ct_srv_dst	integer	No. of connections that contain the same service and destination address in 100 connections according to the last time.
ct_dst_ltm	integer	No. of connections of the same destination address in 100 connections.
ct_src_ltm	integer	No. of connections of the same source address in 100 connections.
ct_src_dport_ltm	integer	No. of connections of the same source address and destination port in 100 connections.
ct_dst_sport_ltm	integer	No. of connections of the same destination address and the source port in 100 connections.
ct_dst_src_ltm	integer	No. of connections of the same source and destination address in in 100 connections.

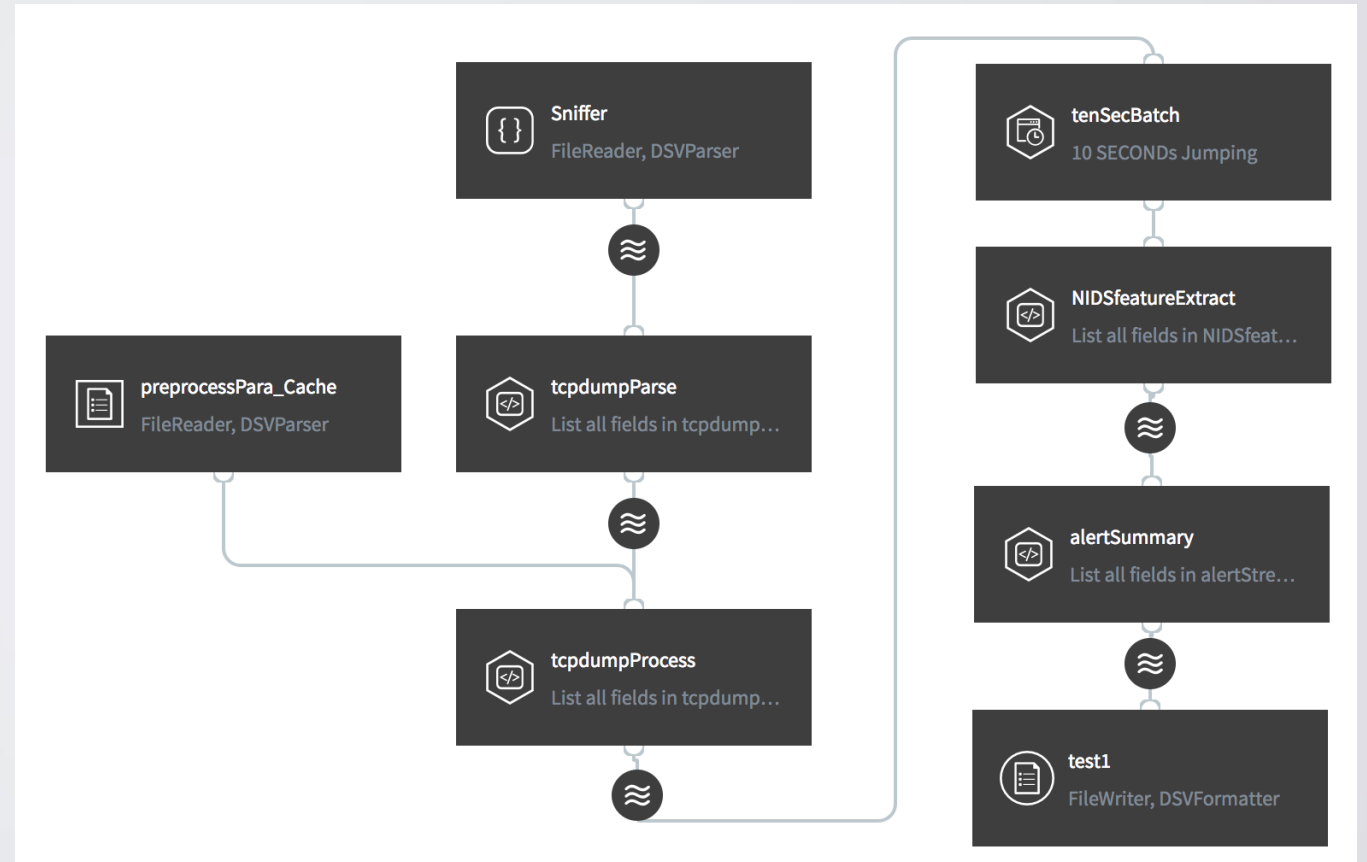
NIDS Task 1: Anomaly Detection on Network Flows

Deploy anomalyDetection application,
and view Flow



NIDS Task 1: Anomaly Detection on Network Flows

- Ingest data
- Filter data fields
- Preprocess raw data
- Aggregate events
- Extract features
- Detect anomalies
- Persist results



NIDS Task 1: Anomaly Detection on Network Flows

- Ingest data

Sniffer

ADAPTER ⓘ

FileReader

Directory ⓘ

./IntelAICon/appData

Wildcard ⓘ

tcpdumpData.csv

Show optional properties

PARSER ⓘ

DSVParser

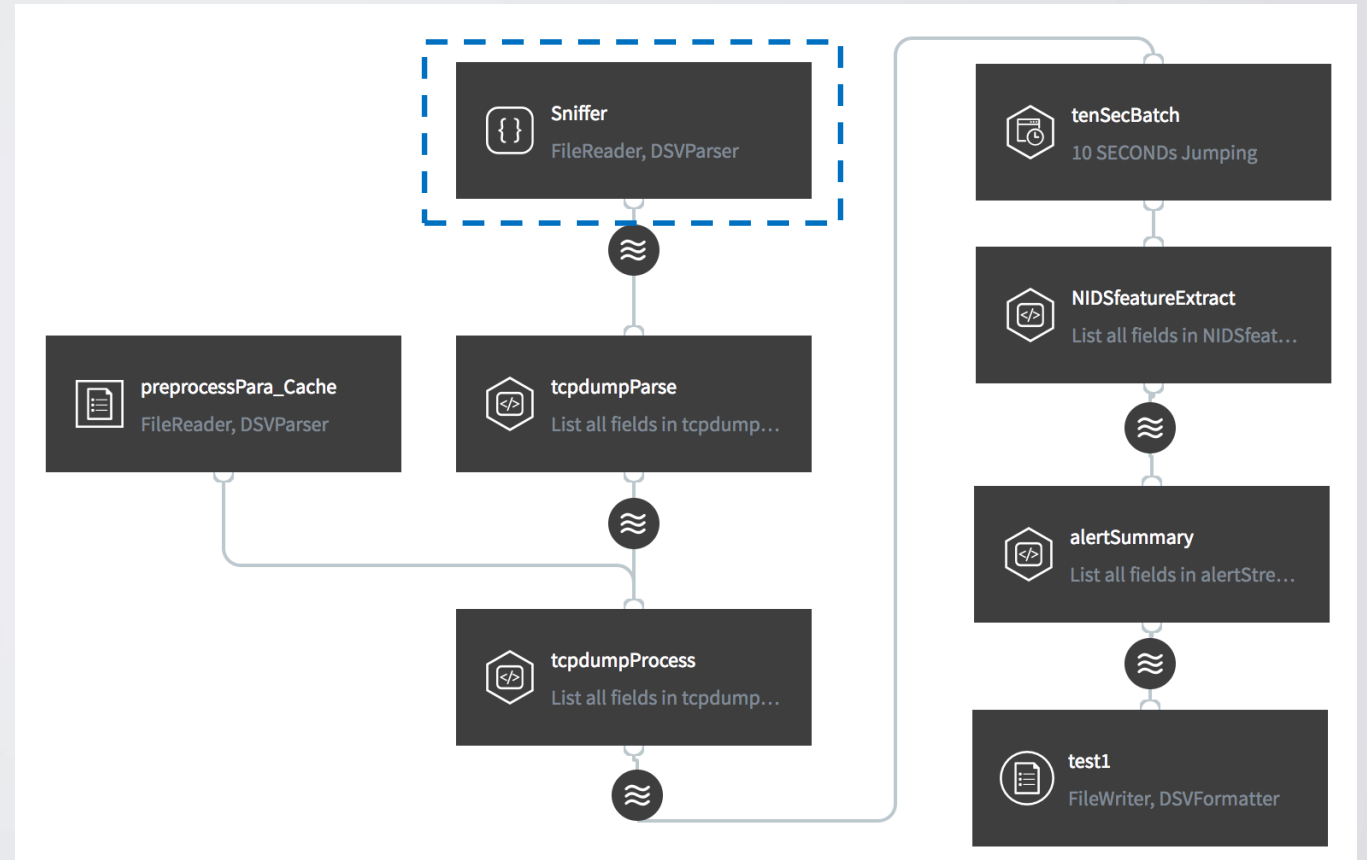
Show optional properties

OUTPUT TO

☐ New Output

☒ Existing Output

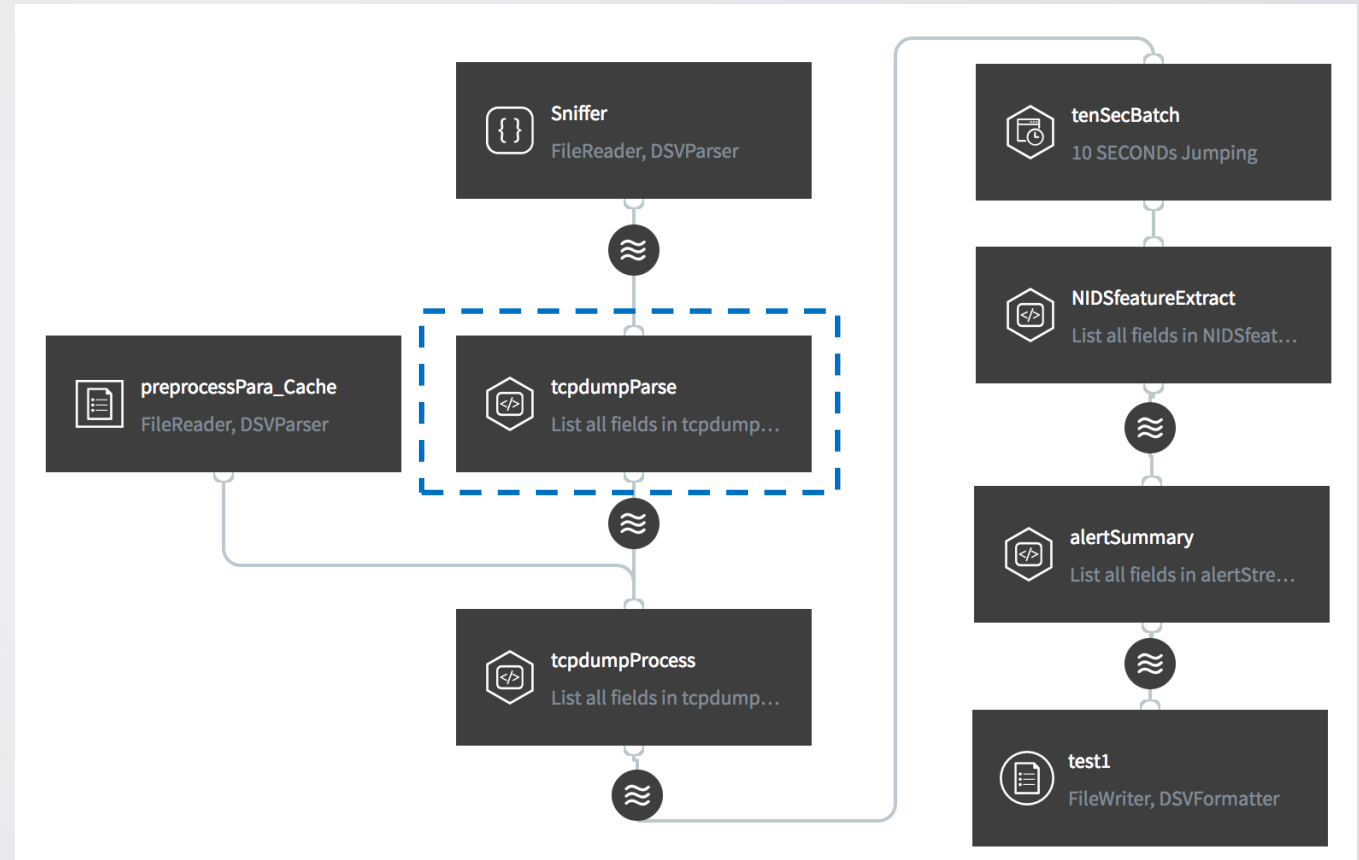
dataStream



NIDS Task 1: Anomaly Detection on Network Flows

- Filter data fields

```
SELECT "NIDS",TO_DATE(TO_LONG(data[0])*1000),
TO_STRING(data[1]), TO_STRING(data[2]),
TO_Double(data[3]),TO_STRING(data[4]),TO_STRING(data[5]),
TO_STRING(data[6]),TO_Double(data[7]),TO_Double(data[8]),
TO_Double(data[9]),TO_Double(data[10]),TO_Double(data[11]),
TO_Double(data[12]),TO_Double(data[13]),TO_Double(data[14]),
TO_Double(data[15]),TO_Double(data[16]),TO_Double(data[17]),
TO_Double(data[18]),TO_Double(data[19]),TO_Double(data[20]),
TO_Double(data[21]),TO_Double(data[22]),TO_Double(data[23]),
TO_Double(data[24]),TO_Double(data[25]),TO_Double(data[26]),
TO_Double(data[27]),TO_Double(data[28]),TO_Double(data[29]),
TO_Double(data[30]),TO_Double(data[31]),TO_Double(data[32]),
TO_Double(data[33]),TO_Double(data[34]),TO_Double(data[35]),
TO_Double(data[36]),TO_Double(data[37]),TO_Double(data[38]),
TO_Double(data[39]),TO_Double(data[40]),TO_Double(data[41]),
TO_Double(data[42]),TO_Double(data[43]),TO_Double(data[44])
FROM dataStream c WHERE PAUSE(15000L, c)
```



NIDS Task 1: Anomaly Detection on Network Flows

- Preprocess raw data
 - Enrich stream with standardization parameters from cache

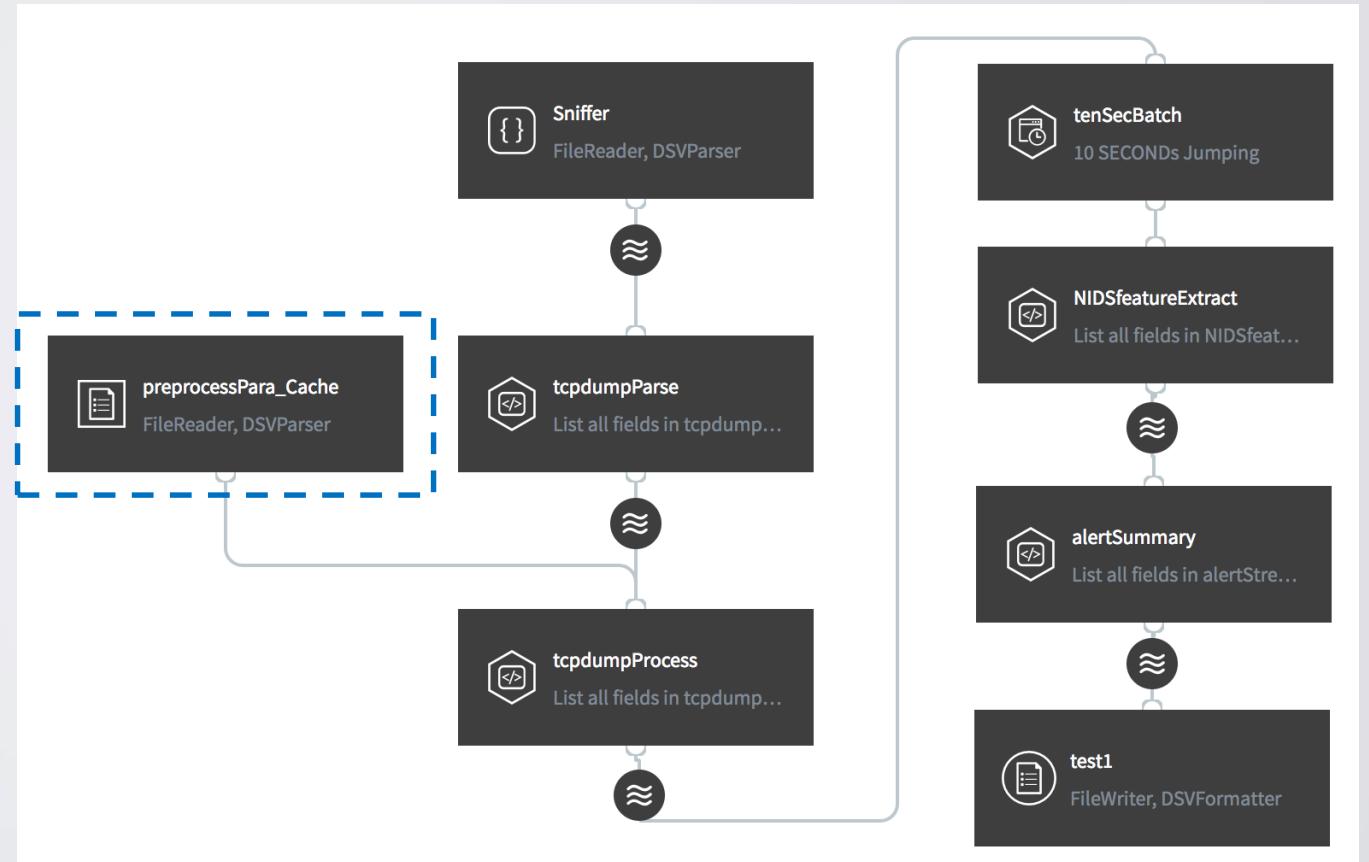
preprocessPara_Cache

Type: preprocessType [HIDE](#)

Key	Field	Type
<input type="text"/>	m_ct_src_ltm	Double
<input type="text"/>	m_ct_srv_dst	Double
<input type="text"/>	m_is_sm_ips_ports	Double
<input type="text"/>	s_dur	Double


QUERY PROPERTIES

Lookup Key name



NIDS Task 1: Anomaly Detection on Network Flows

- Preprocess raw data

 tcpdumpProcess


QUERY

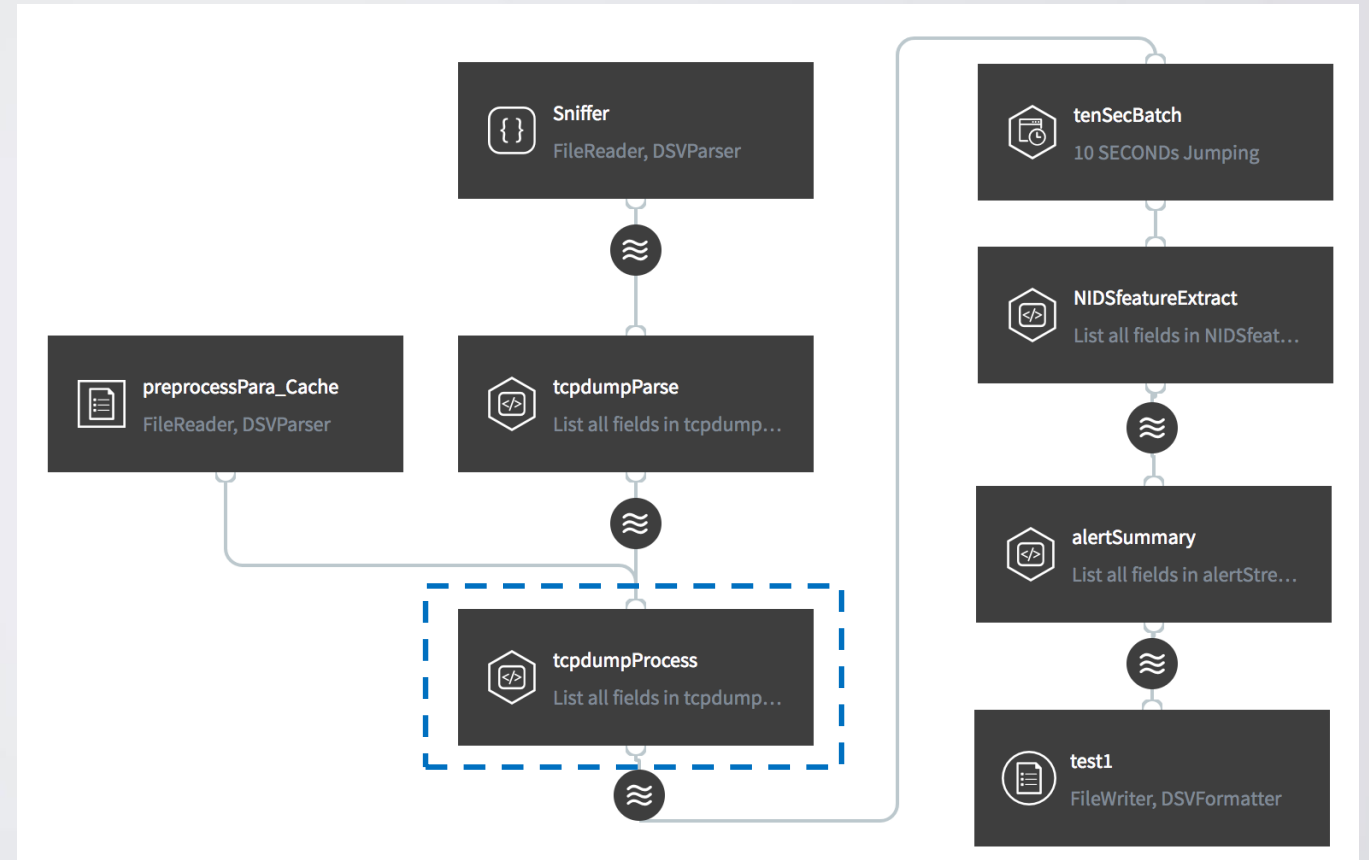
```
select
s.name, s.datetime, s.src,s.dst,
(s.dur-p.m_dur)/p.s_dur,
s.proto, s.service, s.state,
(s.spkts-p.m_spkts)/p.s_spkts,
(s.dpks-p.m_dpks)/p.s_dpks,
(s.sbytes-p.m_sbytes)/p.s_sbytes,
(s.dbytes-p.m_dbytes)/p.s_dbytes,
(s.rate-p.m_rate)/p.s_rate,
(s.sttl-p.m_sttl)/p.s_sttl,
(s.dttl-p.m_dttl)/p.s_dttl,
(s.sload-p.m_sload)/p.s_sload,
(s.dload-p.m_dload)/p.s_dload,
(s.sloss-p.m_sloss)/p.s_sloss,
(s.dloss-p.m_dloss)/p.s_dloss,
(s.sinpkt-p.m_sinpkt)/p.s_sinpkt,
```

OUTPUT TO

☐ New Output

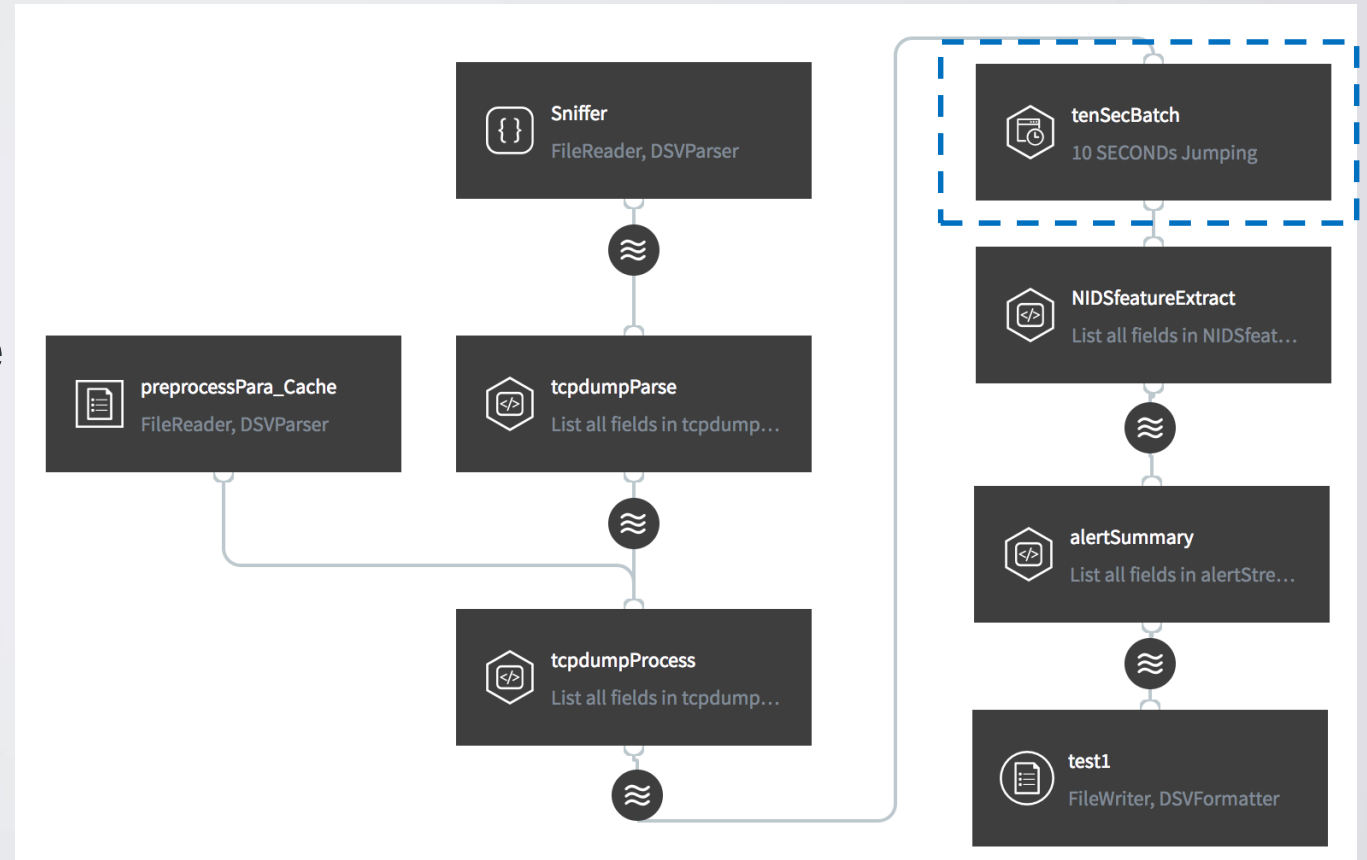
☒ Existing Output

 tcpdumpProcessStream



NIDS Task 1: Anomaly Detection on Network Flows

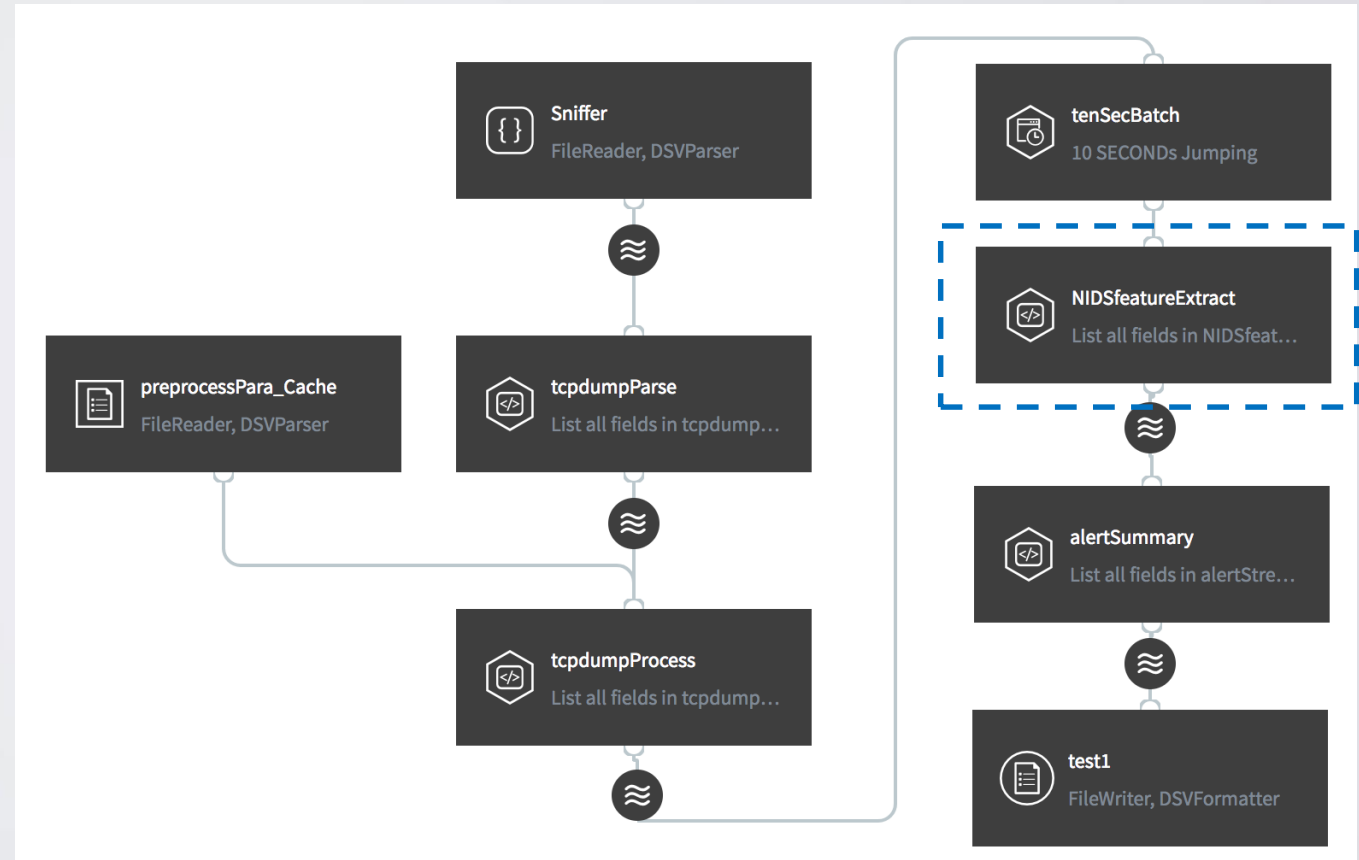
- Aggregate events
 - 10 seconds as observation interval
 - Two adjacent points in time series have 10-second time difference



NIDS Task 1: Anomaly Detection on Network Flows

- Extract features

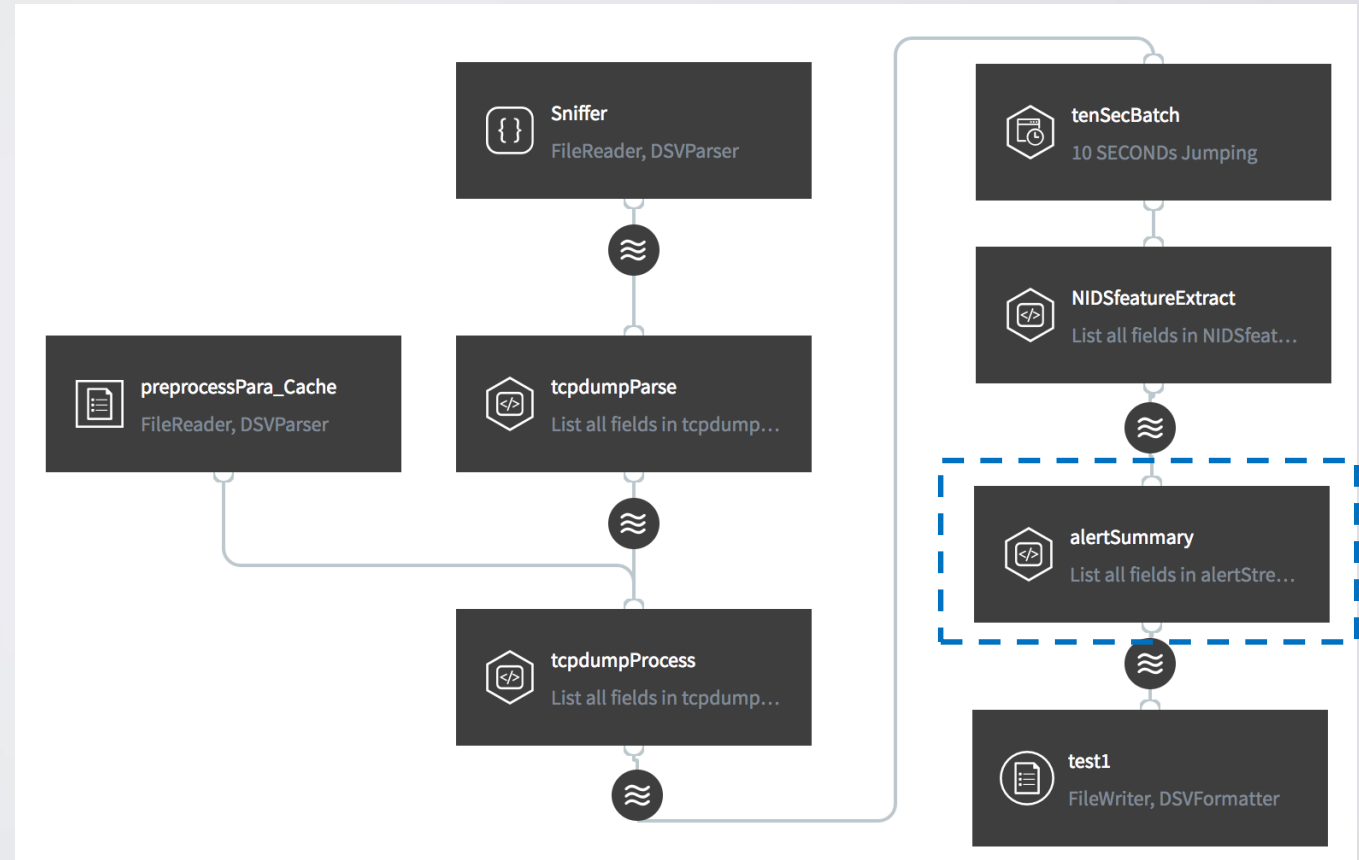
```
select last(datetime) as datetime, last(name) as name,  
count(datetime) as total, list(src) as src, list(dst) as dst, list(dur) as f1,  
list(proto) as f2, list(service) as f3, list(state) as f4, list(spkts) as f5,  
list(dpks) as f6, list(sbytes) as f7, list(dbytes) as f8, list(rate) as f9,  
list(sttl) as f10, list(dtth) as f11, list(sload) as f12, list(dload) as f13,  
list(sloss) as f14, list(dloss) as f15, list(sinpkt) as f16, list(dinpkt) as  
f17, list(sjit) as f18, list(djit) as f19, list(swin) as f20, list(stcpb) as f21,  
list(dtcpb) as f22, list(dwin) as f23, list(tcprtt) as f24, list(synack) as  
f25, list(ackdat) as f26, list(smean) as f27, list(dmean) as f28,  
list(trans_depth) as f29, list(response_body_len) as f30,  
list(ct_srv_src) as f31, list(ct_state_ttl) as f32, list(ct_dst_ltm) as f33,  
list(ct_src_dport) as f34, list(ct_dst_sport) as f35, list(ct_dst_src_ltm)  
as f36, list(is_ftp_login) as f37, list(ct_ftp_cmd) as f38,  
list(ct_flw_http_mthd) as f39, list(ct_src_ltm) as f40, list(ct_srv_dst) as  
f41, list(is_sm_ips_ports) as f42  
from tenSecBatch
```



NIDS Task 1: Anomaly Detection on Network Flows


- Detect anomalies
 - One-class SVM

```
select datetime, name, total, AIDCSVMscore(f1, f2, f3, f4,
f5, f6, f7, f8, f9, f10, f11, f12, f13, f14, f15, f16, f17, f18,
f19, f20, f21, f22, f23, f24, f25, f26, f27, f28, f29, f30, f31,
f32, f33, f34, f35, f36, f37, f38, f39, f40, f41, f42,
'/home/admin/Striim/IntelAICon/appData/arffHeader.txt',
'/home/admin/Striim/IntelAICon/appData/testData.arff',
'/home/admin/Striim/IntelAICon/idsOneClass.model') as
anomalySum, anomalySum.size() as anomalyNum,
anomalyExtract(anomalySum,src) as anomalySrc,
anomalyExtract(anomalySum,dst) as anomalyDst from
NIDSfeatureStream;
```



NIDS Task 1: Anomaly Detection on Network Flows

- Persist results

 test1

Input Stream ≈ alertStream

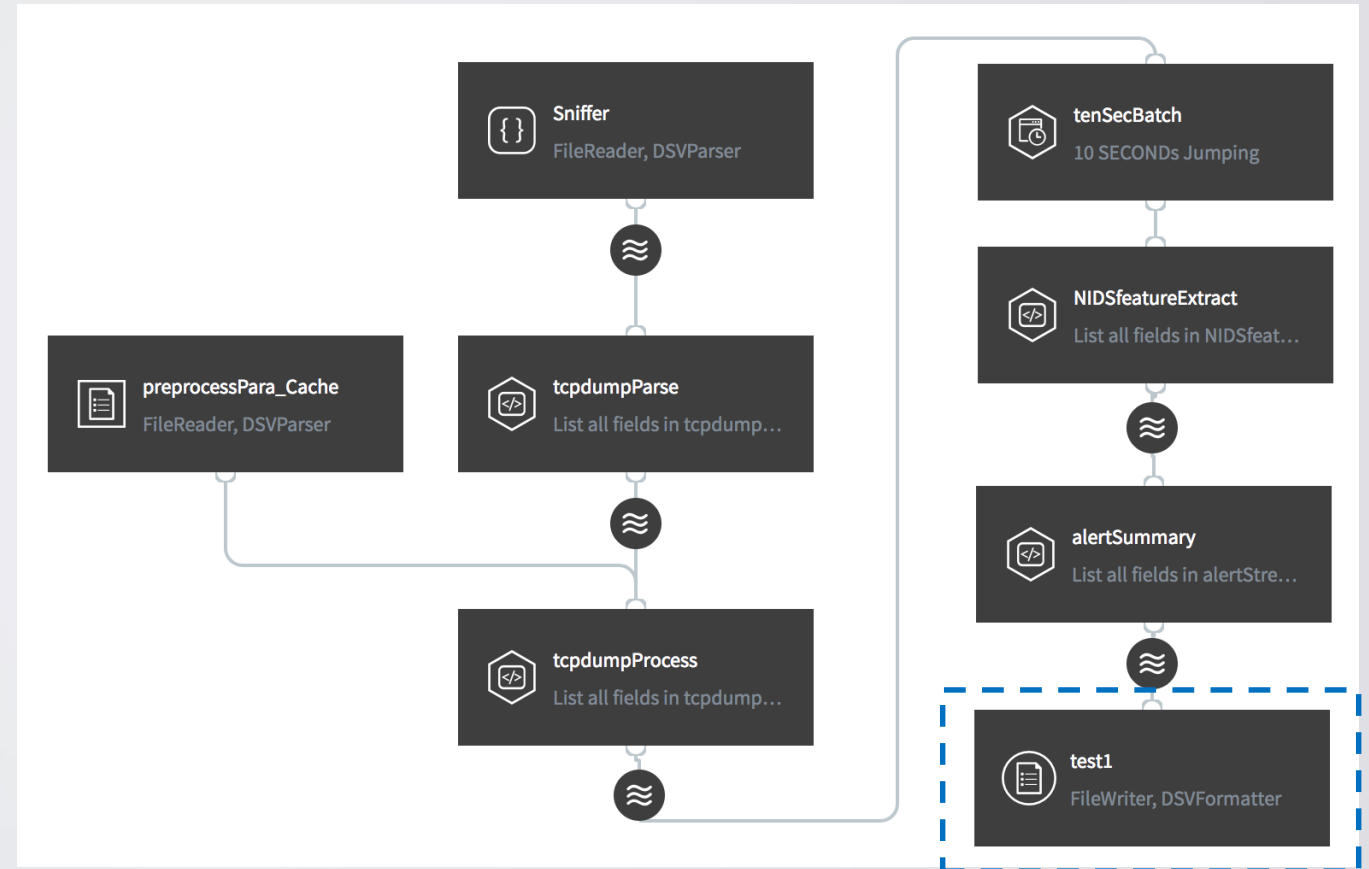
Type alertStream_Type [VIEW](#)

ADAPTER ⓘ FileWriter

File Name alertSummary.csv

[Show optional properties](#)

FORMATTER ⓘ DSVFormatter



NIDS Task 1: Anomaly Detection on Network Flows

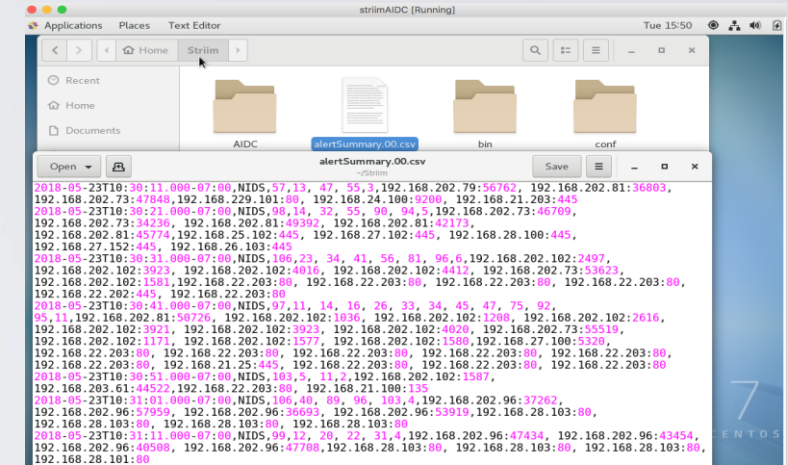
1. Run application to see streaming processing results at each step (Click one stream and then click *Preview on Run*).

Flow: anomalyDetectFlow deployed on: default > Running

Preview data tcpdumpProcessStream

	name	datetime	src	dst	dur	proto	service	state	spkts
100	NIDS	1527096615000	192.168.202.81:53897	192.168.27.100:9200	-0.09159677702666942	tcp	-	FIN	-0.3767
99	NIDS	1527096615000	192.168.202.81:43705	192.168.24.100:445	-0.21175812897854127	tcp	-	FIN	0.1105
98	NIDS	1527096615000	192.168.202.81:54298	192.168.28.100:9200	-0.22496011562553936	udp	dns	CON	-0.5159
97	NIDS	1527096615000	192.168.202.81:53897	192.168.27.100:9200	-0.20778156099921388	tcp	-	FIN	-0.1679

2. Go to /home/admin/Striim to see the persisted results in alertSummary.csv



3. Stop and undeploy the application

Flow: anomalyDetectFlow deployed on: default > Deployed

Undeploy App

Start App

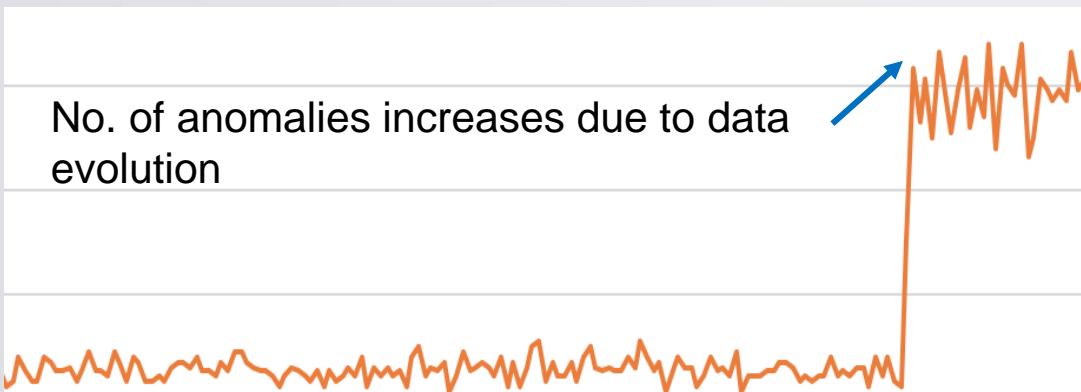
NIDS Task 2 (1): Detect Data Pattern Change

Deploy *anomalyDetection* and then deploy *retrain*
View Flow of *retrain*

Apps ⓘ

anomalyDetection	retrain
1 Source, 0 WActionStores	0 Sources, 0 WActionStores
0 msg/s 0 WActions	0 msg/s 0 WActions
IntelAIDC	IntelAIDC

[Manage Flow](#)
[Monitor App](#)
[Export TQL](#)
[Start](#)
[Undeploy](#)



NIDS Task 2 (1): Detect Data Pattern Change

- Difference time series
- Aggregate recent time events and prepare algorithm input
- Detect time series peaks



NIDS Task 2 (1): Detect Data Pattern Change

- Difference time series

 twoAlertEvent

Mode ⓘ

Sliding

 alertDifference

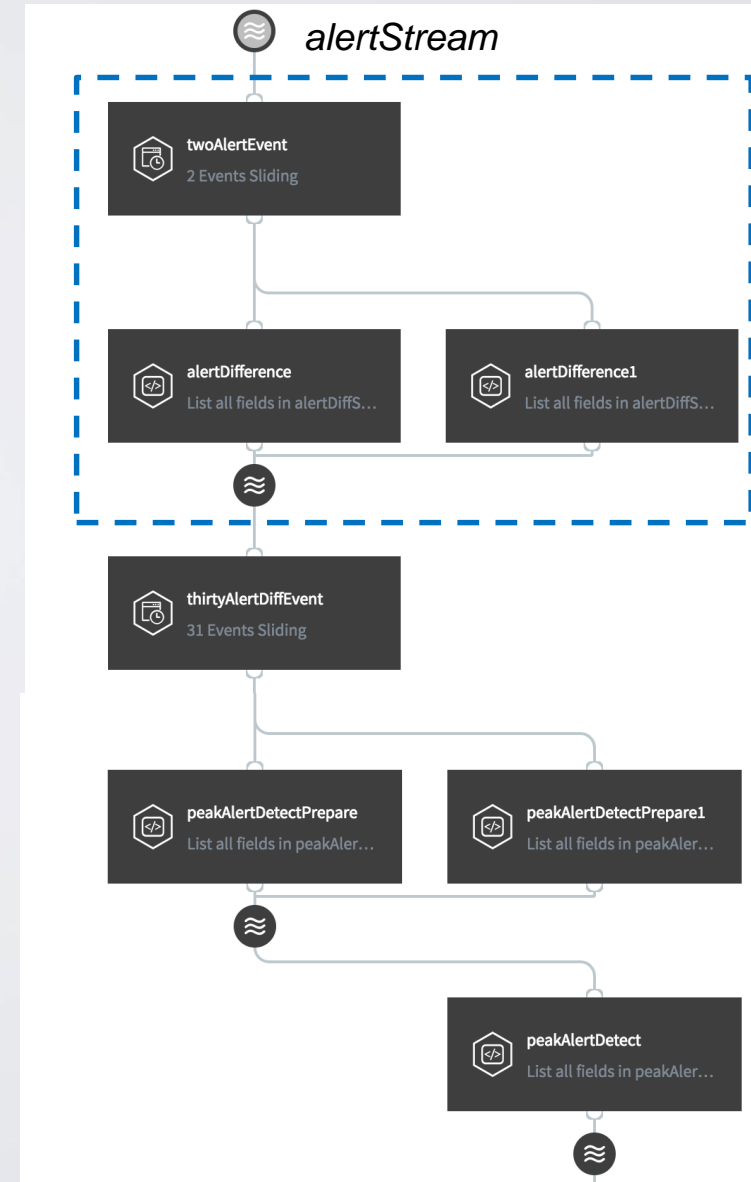
QUERY

```
SELECT last(datetime) as datetime, name, to_double(last(total)-
first(total)) as totalDiff, to_double(last(anomalyNum)-
first(anomalyNum)) as anomalyDiff FROM twoAlertEvent having
count(*) = 2
```

 alertDifference1


QUERY

```
SELECT last(datetime) as datetime, name, 0.0 as totalDiff, 0.0 as
anomalyDiff FROM twoAlertEvent having count(*) < 2
```



NIDS Task 2 (1): Detect Data Pattern Change

- Aggregate recent time events
 - Constrain peak detection on

 **thirtyAlertDiffEvent**

Mode ⓘ

Sliding

Partition by

INPUT FROM

Input Stream ⓘ

≈ alertDiffStream

Type

alertDiffStream_Type [VIEW](#)


SIZE OF WINDOW ⓘ

☐ Time

☒ Count


Events

31

 **peakAlertDetectPrepare**

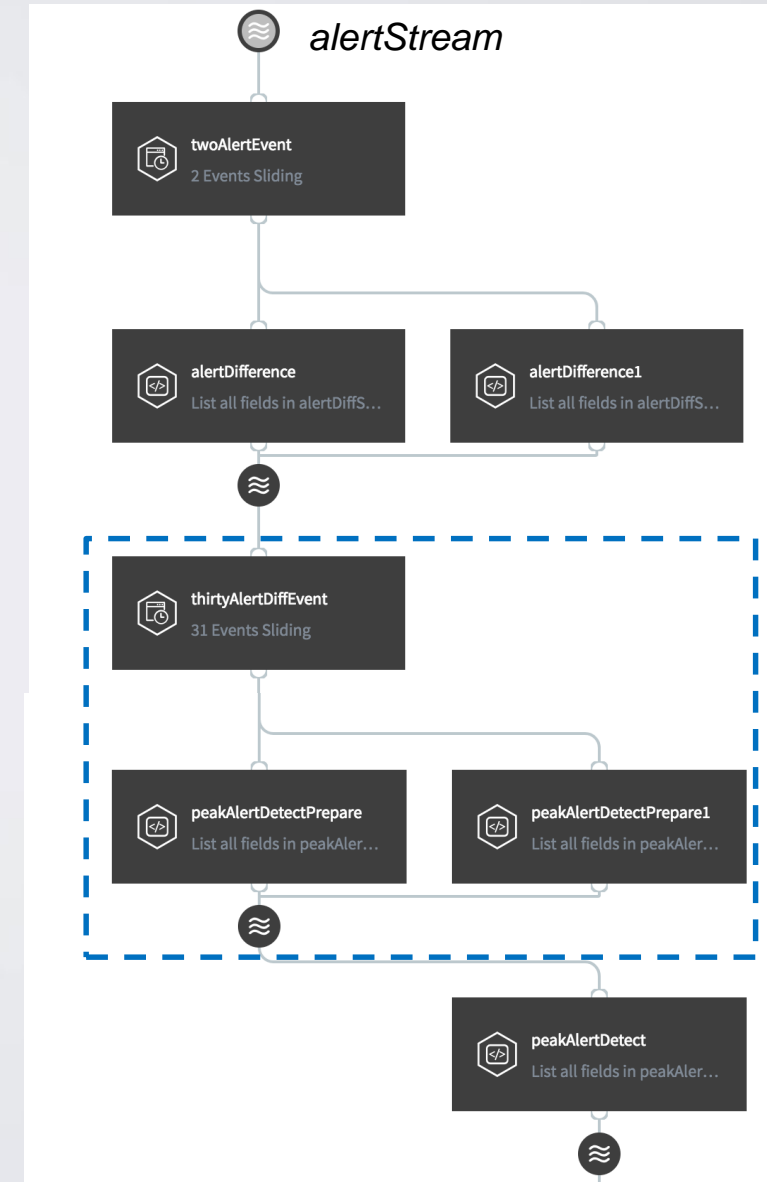
QUERY

```
SELECT last(datetime) as datetime, name, list(anomalyDiff) as anomalyNum FROM thirtyAlertDiffEvent having count(*) = 31
```

 **peakAlertDetectPrepare1**

QUERY

```
SELECT last(datetime) as datetime, name, list(0.0) as anomalyNum FROM thirtyAlertDiffEvent having count(*) < 31
```



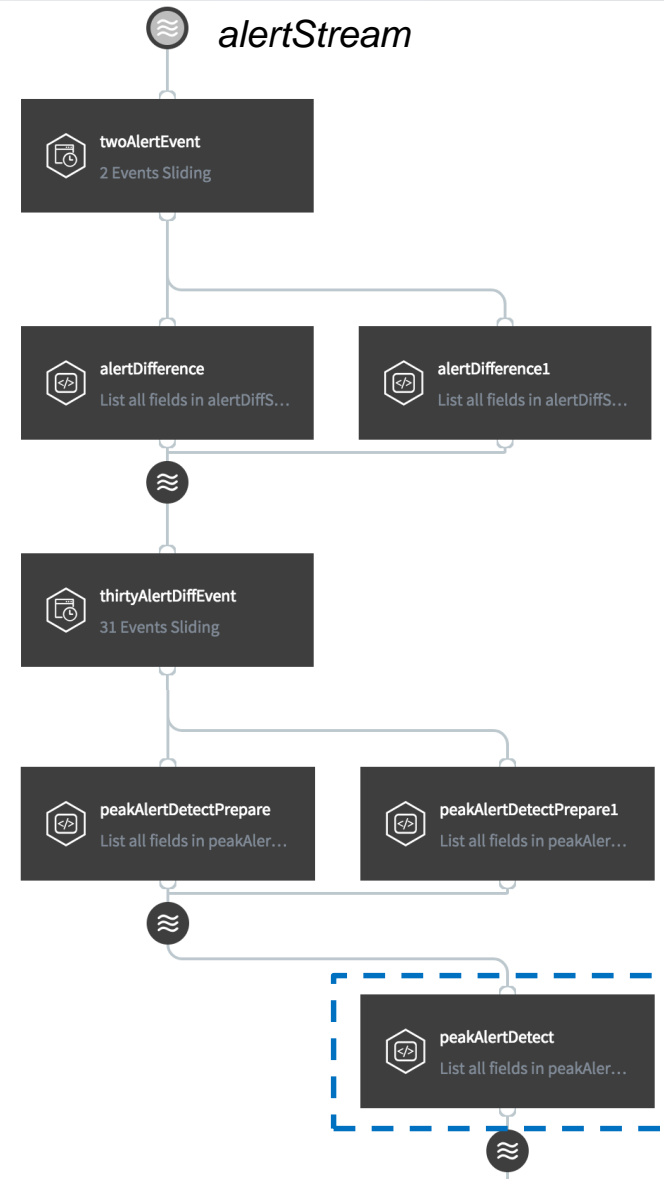
NIDS Task 2 (1): Detect Data Pattern Change

- Detect time series peaks
 - Calculate z-score of the 31th event in the sliding window

peakAlertDetect

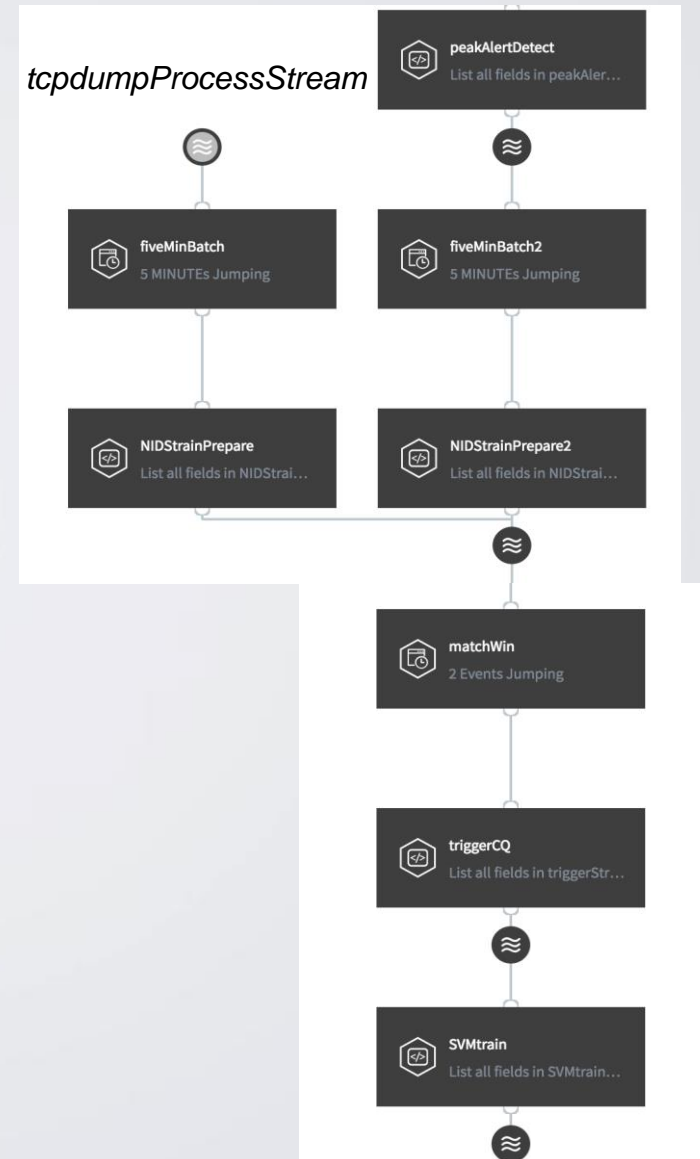
QUERY

```
SELECT datetime as datetime, name as name, peakDetect(anomalyNum,  
5) as anomalyPeak  
FROM peakAlertDetectStream
```



NIDS Task 2 (2): Retrain Model

- Aggregate new training data
- Aggregate peak signals
- Join two parallel flows
- Cancel/trigger retraining



NIDS Task 2 (2): Retrain Model

- Aggregate new training data

fiveMinBatch

Mode ⓘ Jumping

Partition by

INPUT FROM

Input Stream ⓘ tcpdumpProcessStream

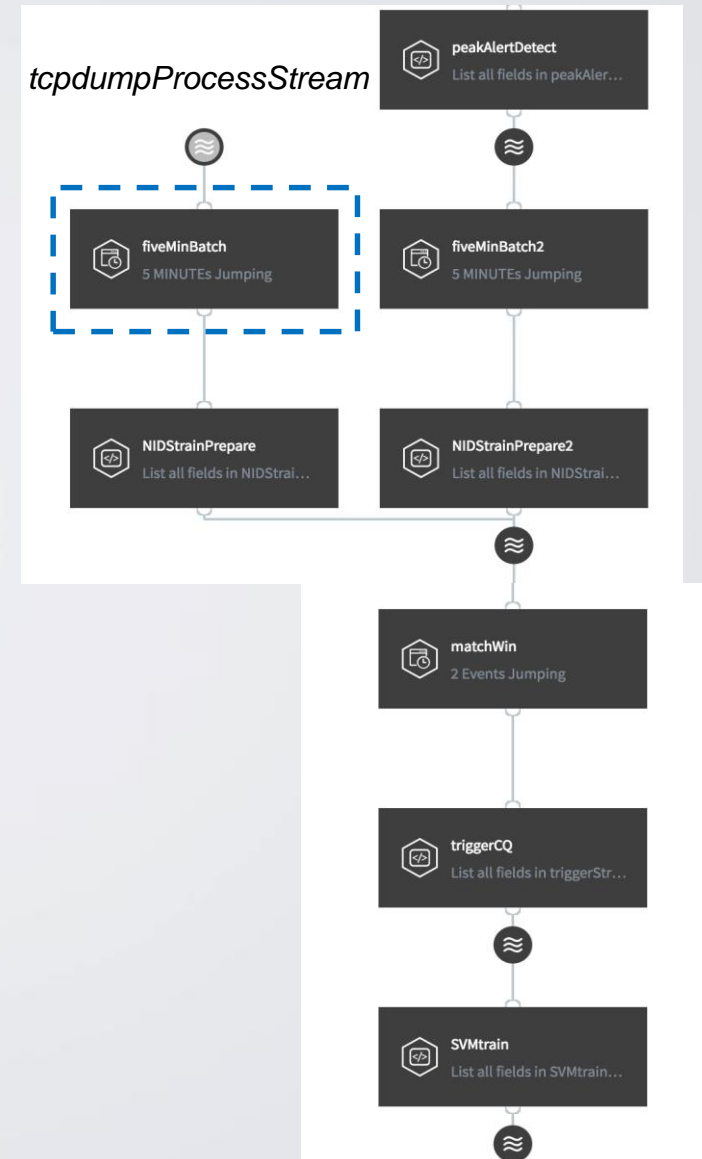
Type tcpdumpType [VIEW](#)

SIZE OF WINDOW ⓘ

☒ Time


Time 5 MINUTE

Event Time



NIDS Task 2 (2): Retrain Model

- Aggregate peak signals

 **fiveMinBatch2**

Mode ⓘ

Jumping ▼

Partition by

INPUT FROM

Input Stream ⓘ

≈ peakAlertStream ▼

Type

peakAlertStream_Type [VIEW](#)

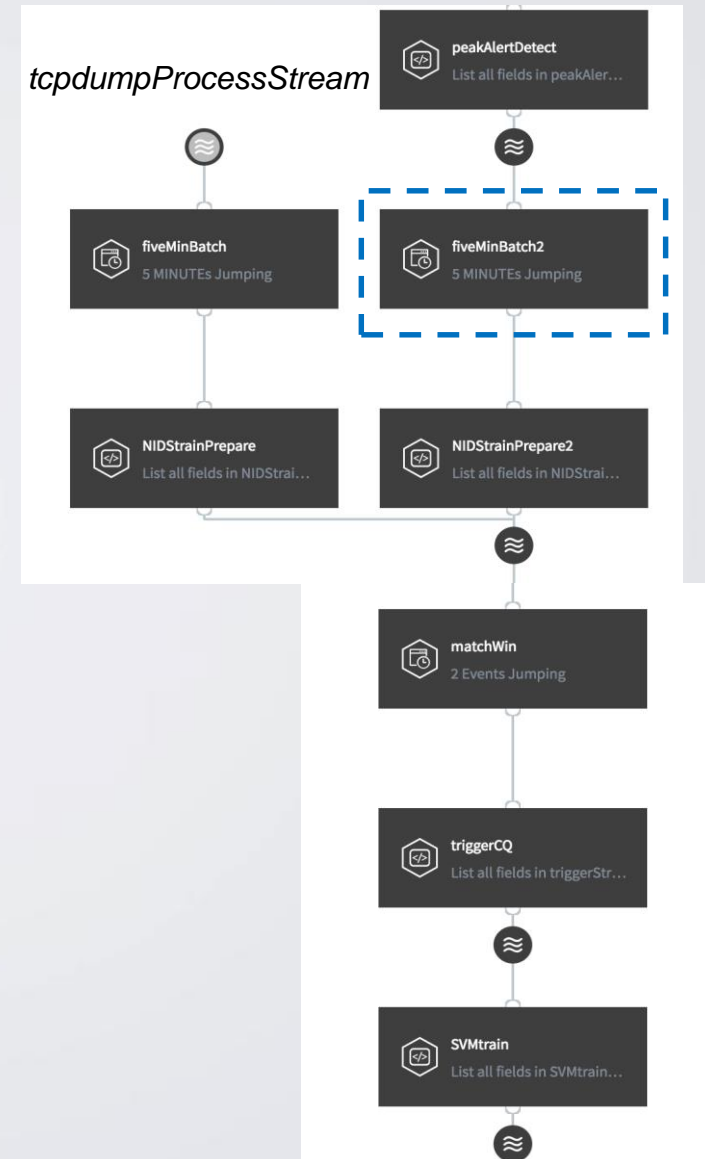
SIZE OF WINDOW ⓘ

☒ Time

Time

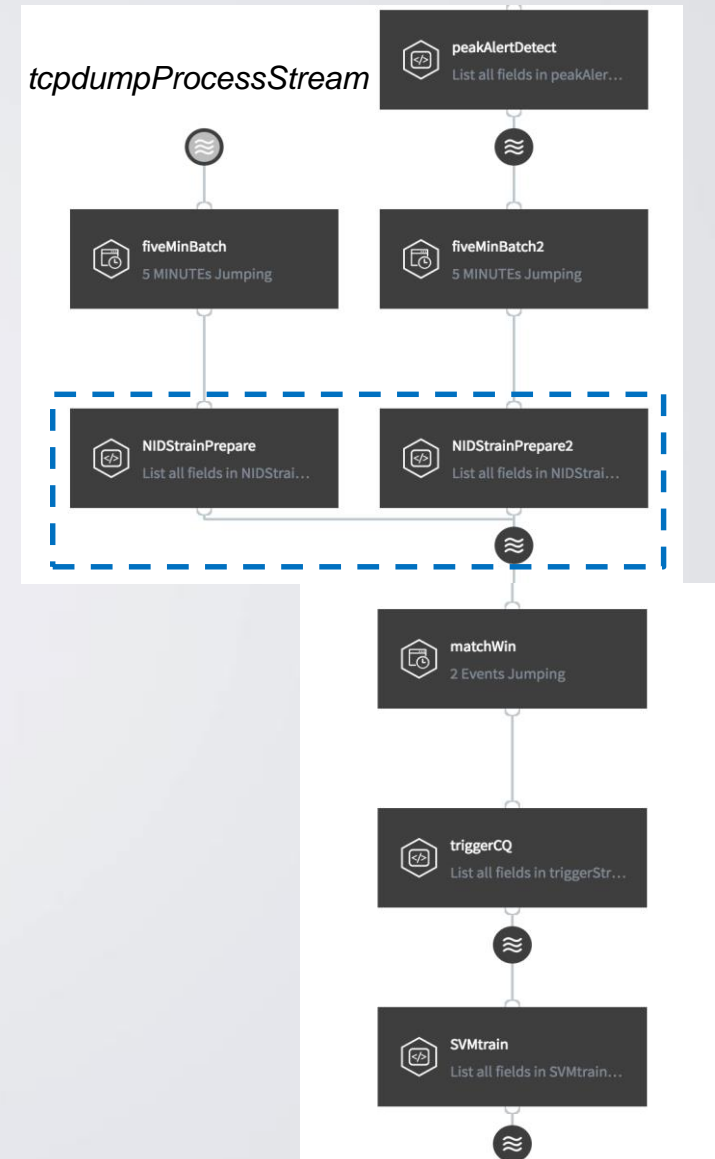
5 MINUTE ▼

Event Time ▼



NIDS Task 2 (2): Retrain Model

- Join two parallel flows
 - Features from *NIDStrainPrepare*
 - Data change signal from *NIDStrainPrepare1*
 - Insert into the same stream



NIDS Task 2 (2): Retrain Model

- Cancel/trigger retraining
 - *CREATE JUMPING WINDOW matchWin OVER NIDStrainDataStream KEEP 2 rows WITHIN 30 second;*

☒ Advanced

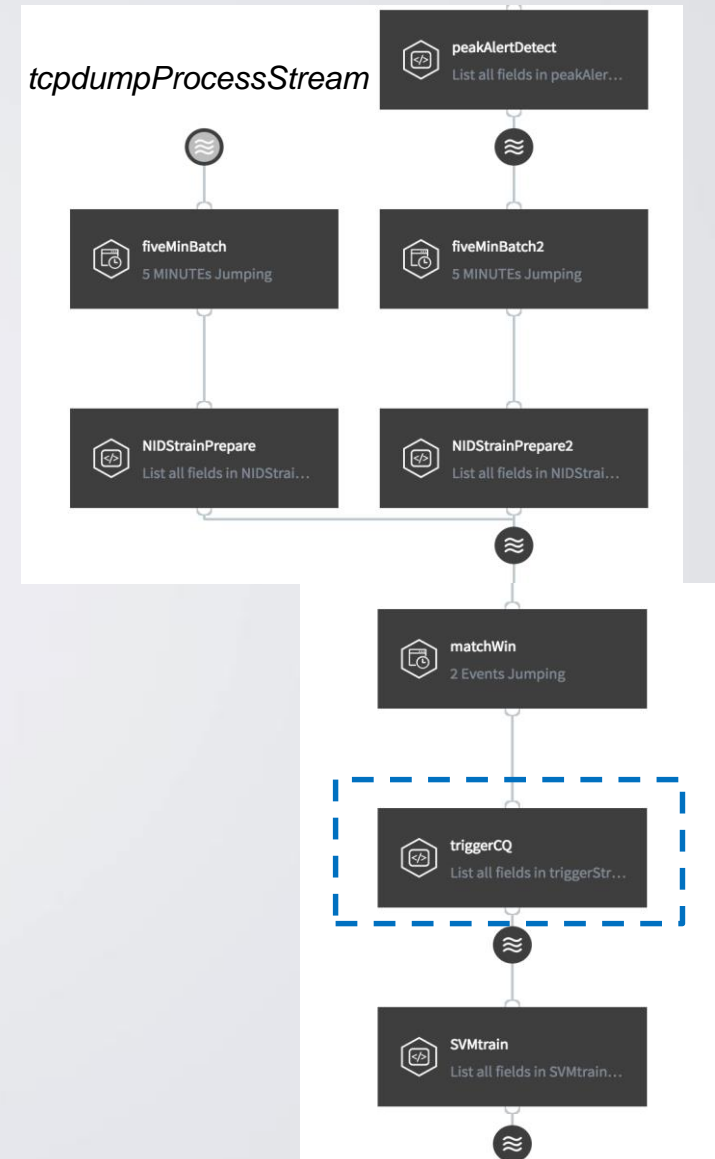
Time	<input type="text"/>	SECOND	▼
Events	<input type="text" value="2"/>		×
Timeout	<input type="text" value="30"/>	SECOND	▼



NIDS Task 2 (2): Retrain Model

- Cancel/trigger retraining
 - Select fields from upstreams

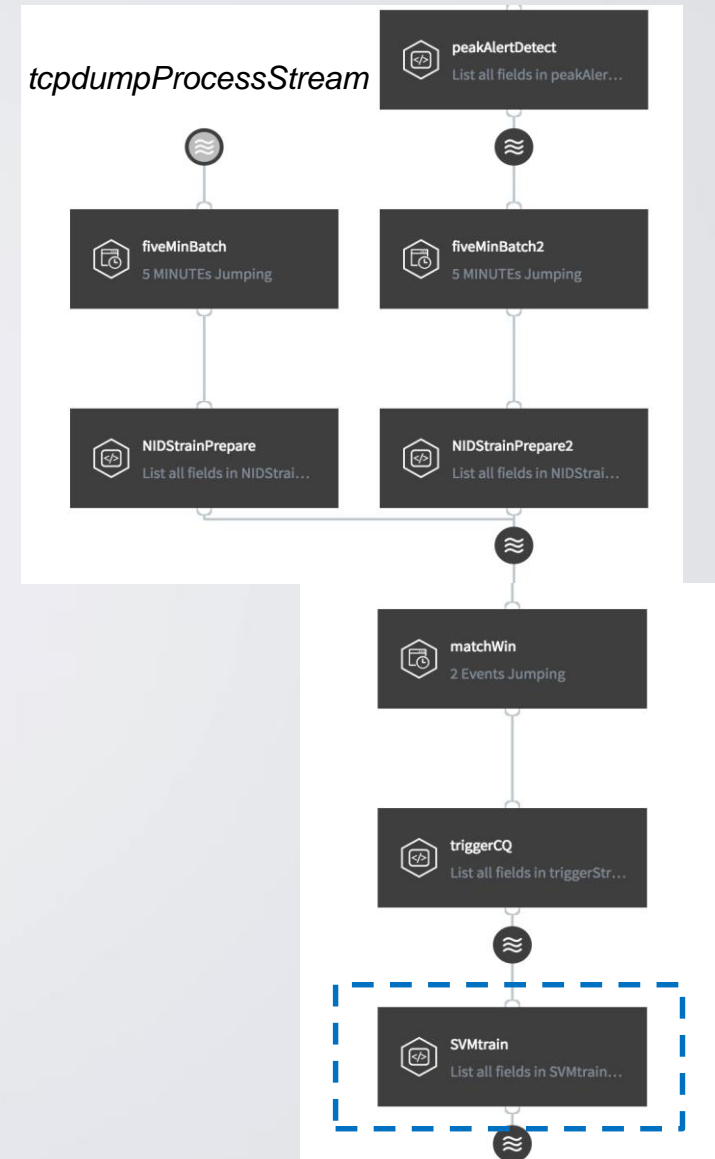
SELECT first(name) as name, first(datetime) as ts1, last(datetime) as ts2, first(total) as total1, last(total) as total2, first(triggerFlag) as flag1, last(triggerFlag) as flag2, first(f1) as f1, first(f2) as f2, first(f3) as f3, first(f4) as f4, first(f5) as f5, first(f6) as f6, first(f7) as f7, first(f8) as f8, first(f9) as f9, first(f10) as f10, first(f11) as f11, first(f12) as f12, first(f13) as f13, first(f14) as f14, first(f15) as f15, first(f16) as f16, first(f17) as f17, first(f18) as f18, first(f19) as f19, first(f20) as f20, first(f21) as f21, first(f22) as f22, first(f23) as f23, first(f24) as f24, first(f25) as f25, first(f26) as f26, first(f27) as f27, first(f28) as f28, first(f29) as f29, first(f30) as f30, first(f31) as f31, first(f32) as f32, first(f33) as f33, first(f34) as f34, first(f35) as f35, first(f36) as f36, first(f37) as f37, first(f38) as f38, first(f39) as f39, first(f40) as f40, first(f41) as f41, first(f42) as f42 from matchWin having count(*) = 2



NIDS Task 2 (2): Retrain Model

- Cancel/trigger retraining
 - If there is data change signal, trigger retraining, otherwise cancel it.

```
SELECT ts1, ts2, flag2 AS signal,  
CASE WHEN signal > 0 THEN  
AIDCSVMtrain(f1, f2, f3, f4, f5, f6, f7, f8, f9, f10, f11, f12, f13, f14, f15, f16,  
f17, f18, f19, f20, f21, f22, f23, f24, f25, f26, f27, f28, f29, f30, f31, f32, f33,  
f34, f35, f36, f37, f38, f39, f40, f41, f42,  
'/home/admin/Striim/IntelAICon/appData/arffHeader.txt',  
'/home/admin/Striim/IntelAICon/appData/trainData.arff', '-S 2 -K 2 -D 3 -G  
0.1 -R 0.0 -N 0.1 -M 40.0 -C 1.0 -E 0.001 -P 0.1',  
'/home/admin/Striim/IntelAICon/idsOneClass.model')  
ELSE 1  
END as status,  
CASE WHEN signal > 0 THEN  
'retrain'  
ELSE 'model serving'  
END as retrainMsg  
FROM triggerStream;
```



NIDS Task 3 (1): Create WactionStores and Alerts

Deploy *monitor* application
(*anomalyDetection* and *retrain* have been
deployed in Task 2)

View Flow of *monitor*

● monitor

0 Sources, 2 WActionStores

0 msg/s 1775 WActions

IntelAIDC

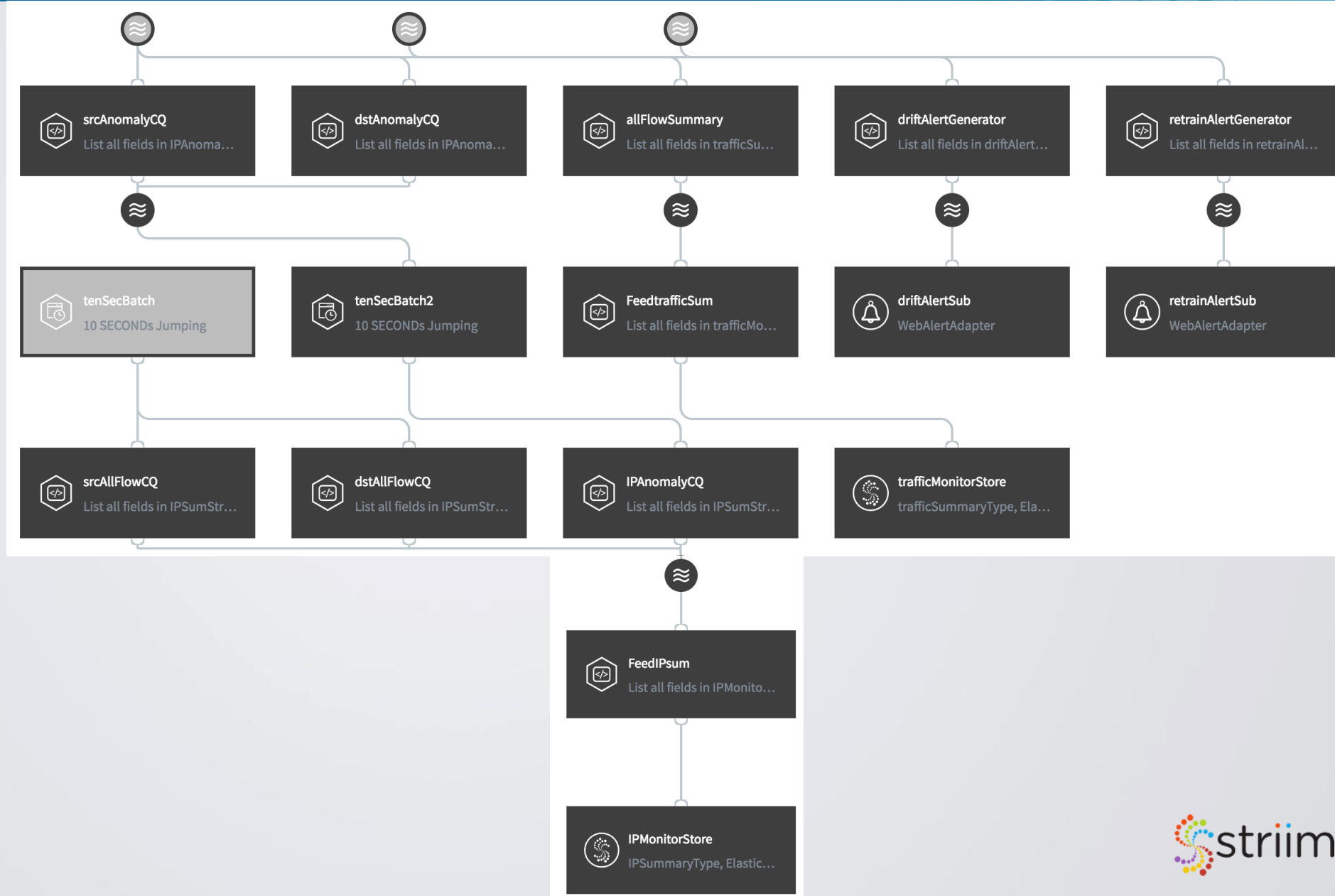
Manage Flow

Monitor App

Export TQL

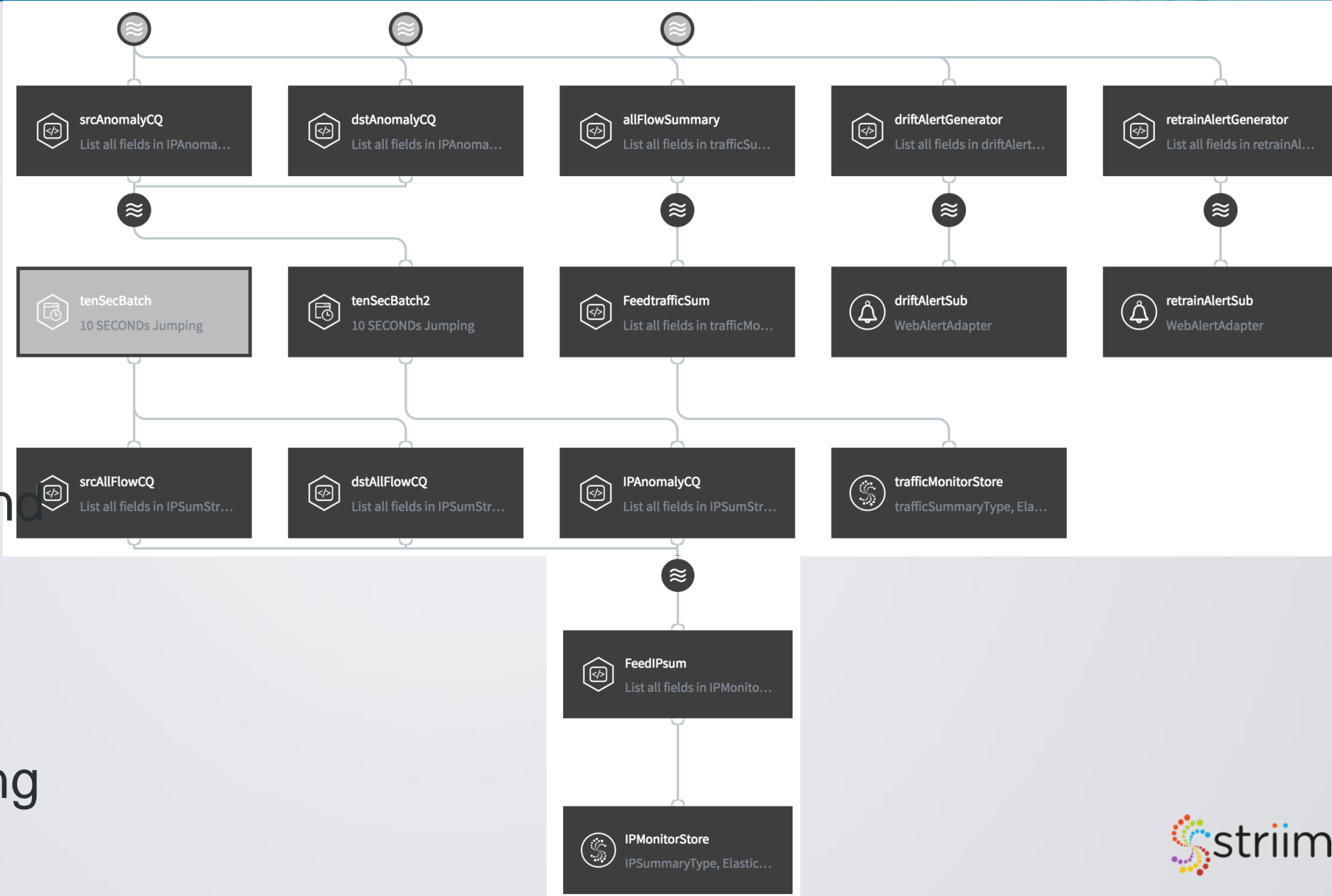
Start

Undeploy



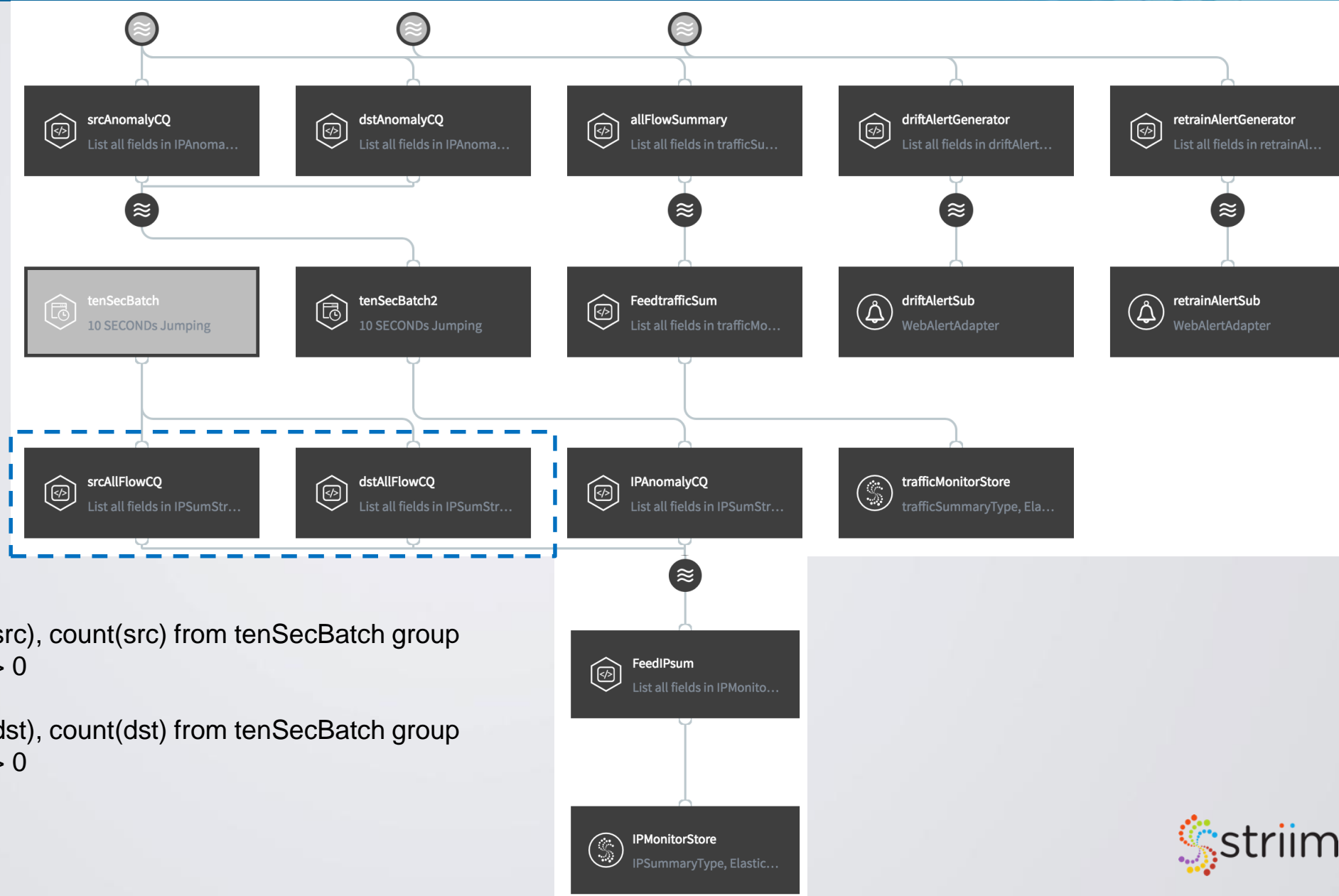
NIDS Task 3 (1): Create WactionStores and Alerts

- Monitor traffic (normal and abnormal) sources and destinations
- Monitor No. of network flows and anomalies
- Alert on data pattern change
- Alert on retraining



NIDS Task 3 (1): Create WactionStores and Alerts

- Monitor traffic sources and destinations

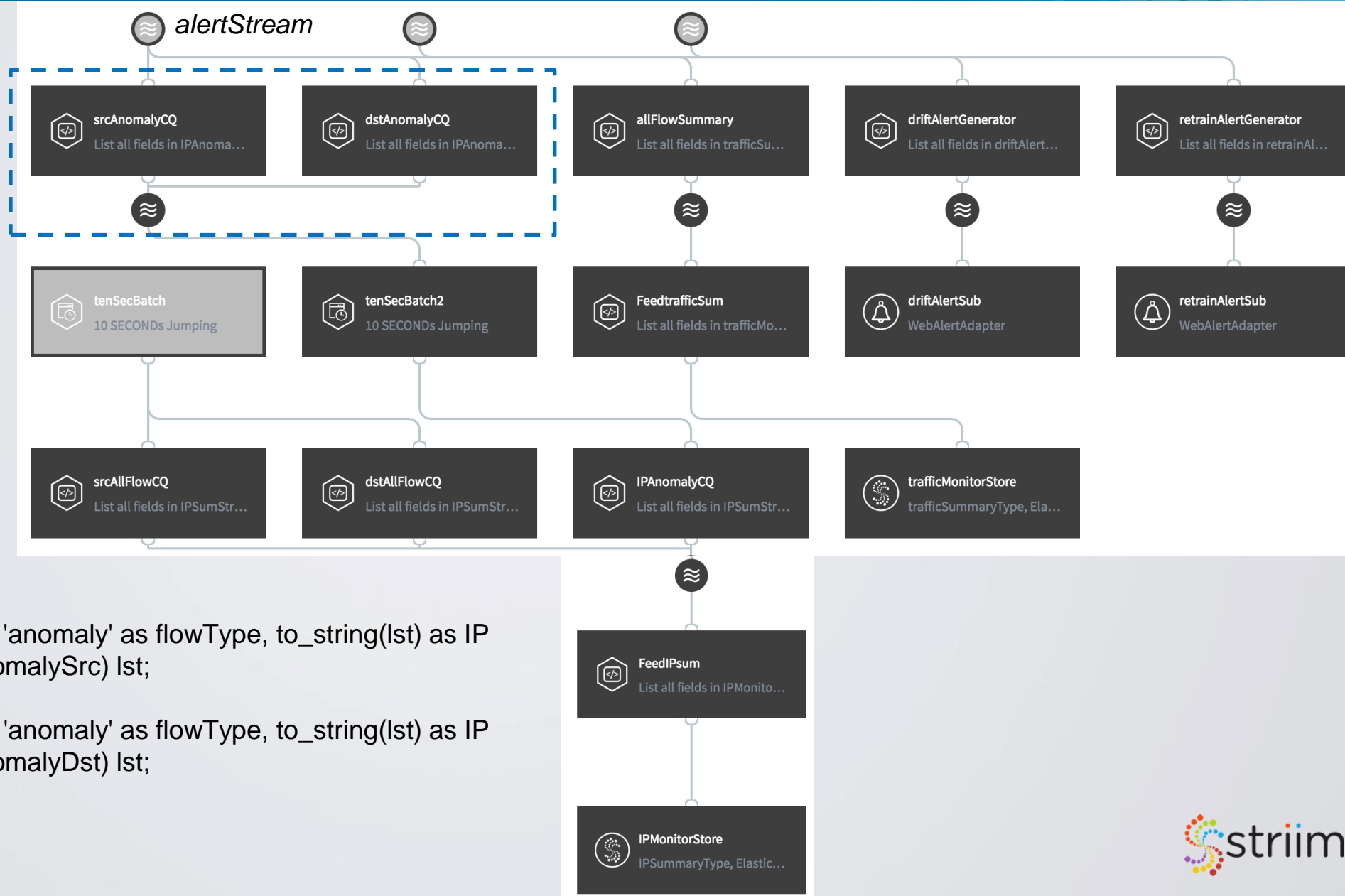


select datetime, 'srcIP', 'all', first(src), count(src) from tenSecBatch group by src, datetime having count(*) > 0

select datetime, 'dstIP', 'all', first(dst), count(dst) from tenSecBatch group by dst, datetime having count(*) > 0

NIDS Task 3 (1): Create WactionStores and Alerts

- Monitor abnormal traffic sources and destinations

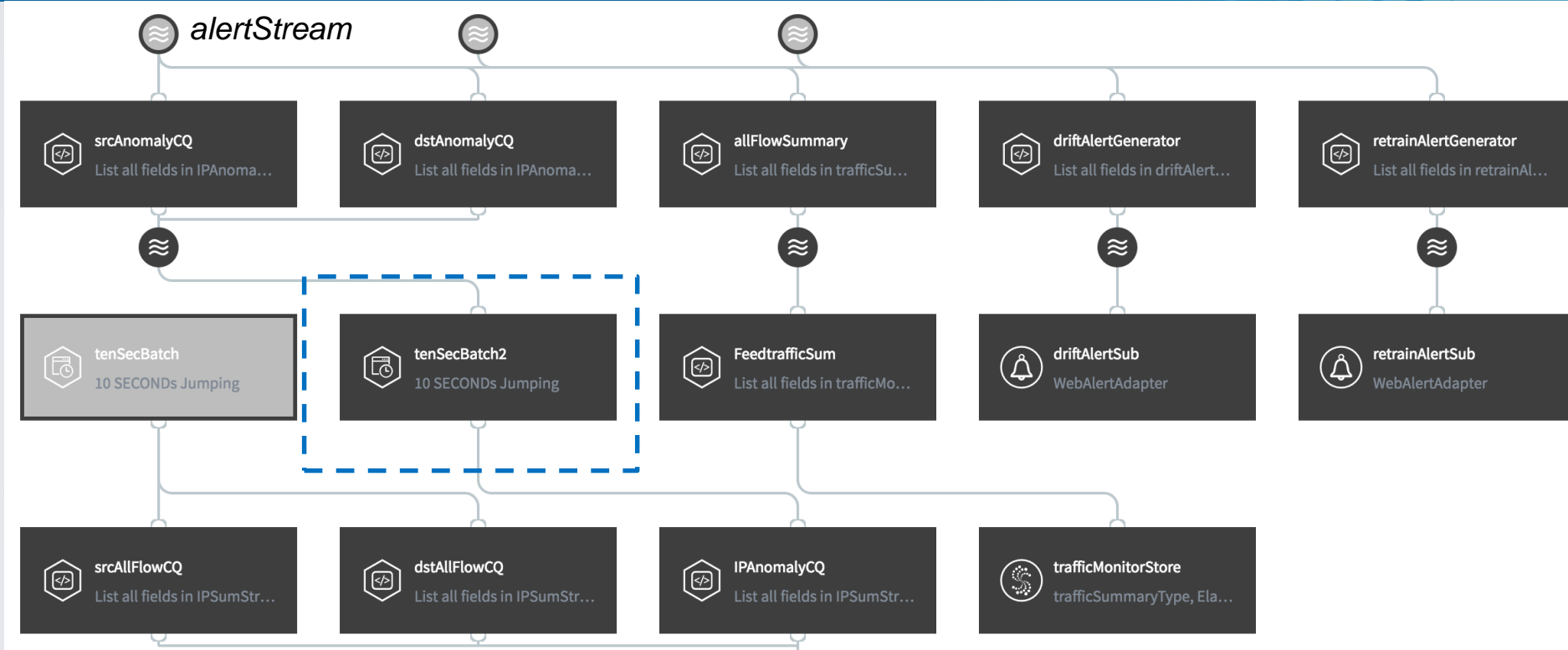


select datetime, 'srcIP' as name, 'anomaly' as flowType, to_string(lst) as IP
from alertStream s, iterator(s.anomalySrc) lst;

select datetime, 'dstIP' as name, 'anomaly' as flowType, to_string(lst) as IP
from alertStream s, iterator(s.anomalyDst) lst;

NIDS Task 3 (1): Create WactionStores and Alerts

- Monitor abnormal traffic sources and destinations



tenSecBatch2

Mode ⓘ

Jumping ▼

SIZE OF WINDOW ⓘ

Time

Time

10

SECOND ▼

Event Time ▼

On

datetime × ▼

FeedIPsum

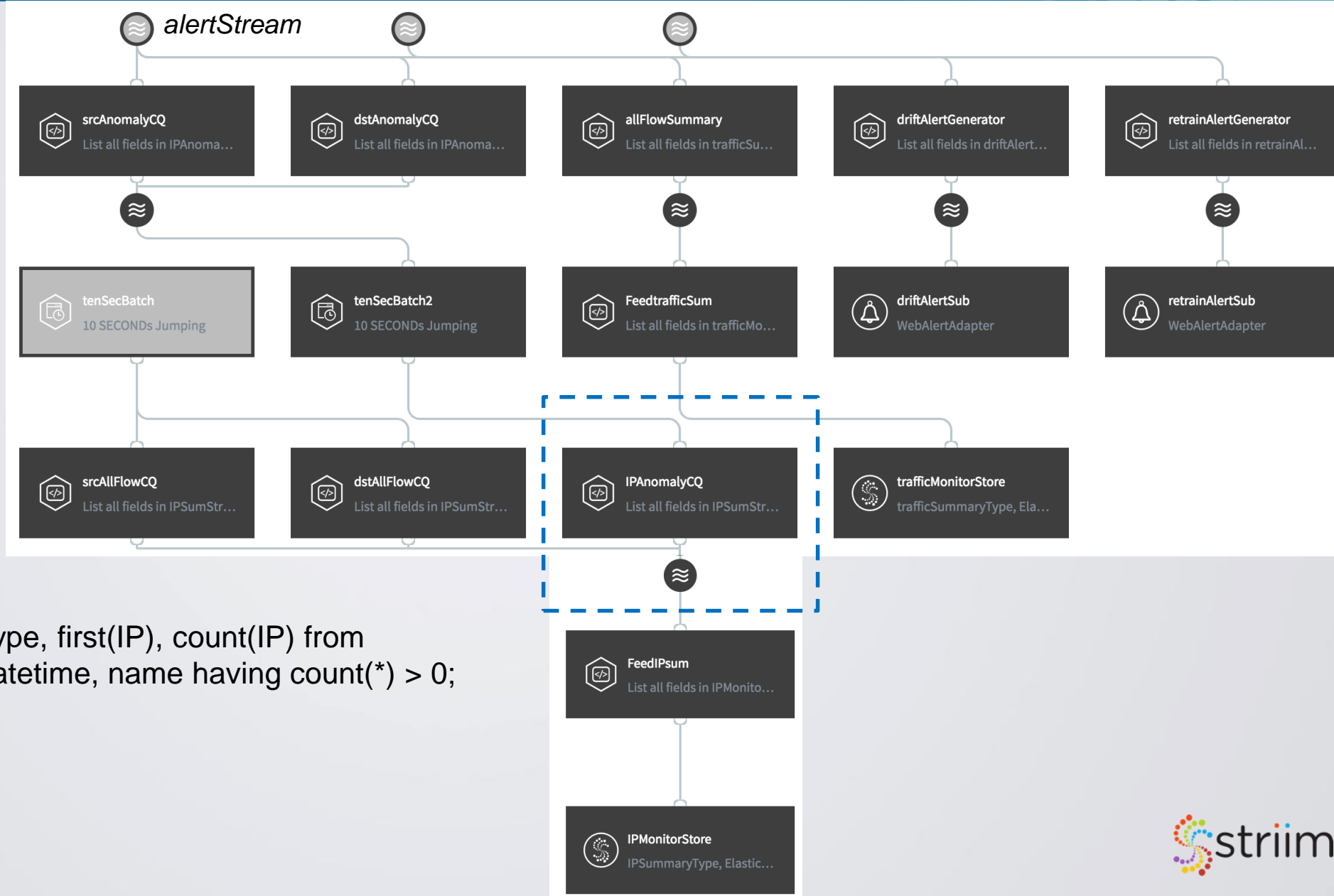
List all fields in IPMonito...

IPMonitorStore

IPSummaryType, Elastic...

NIDS Task 3 (1): Create WactionStores and Alerts

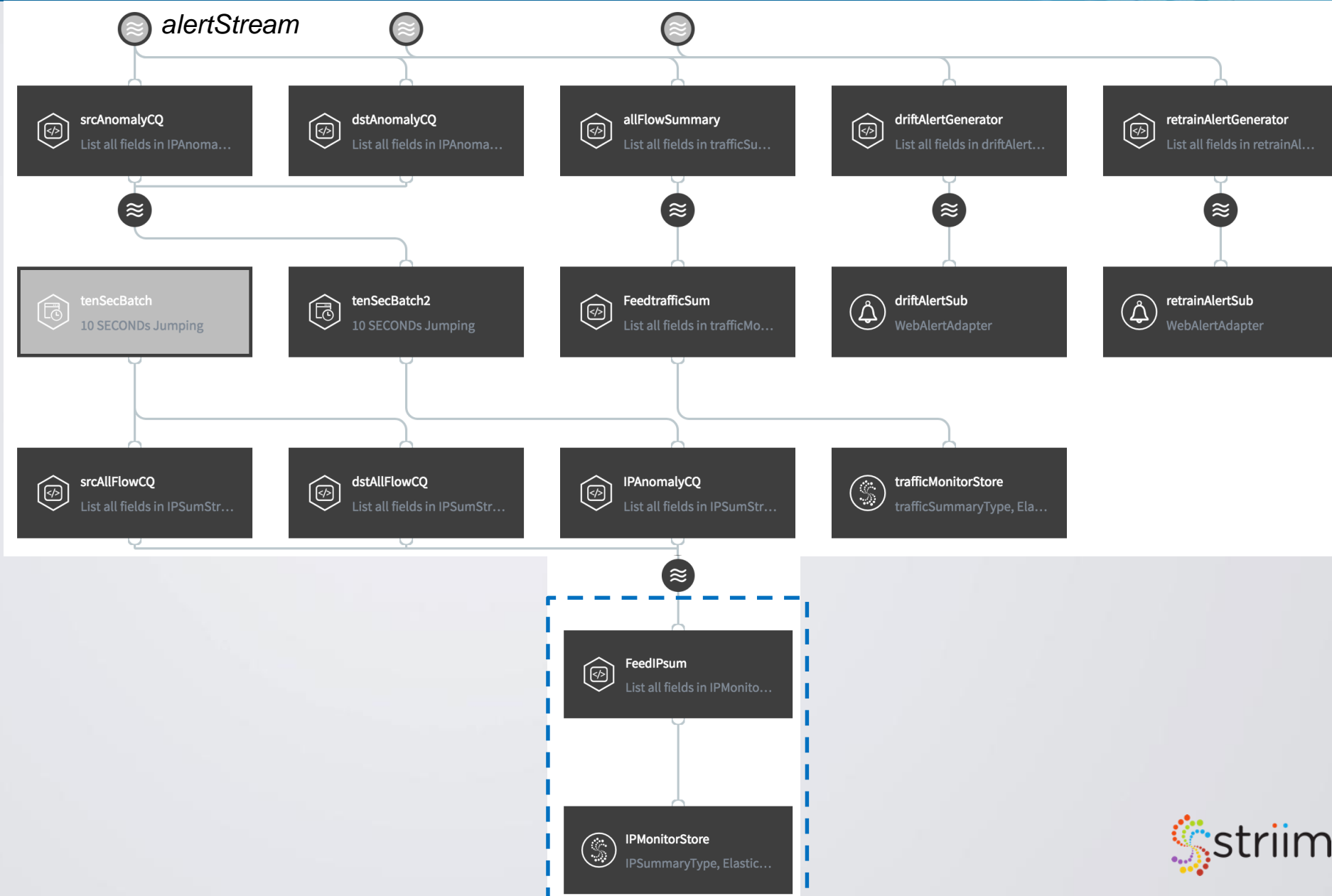
- Monitor abnormal traffic sources and destinations



select datetime, name, flowType, first(IP), count(IP) from
tenSecBatch2 group by IP, datetime, name having count(*) > 0;

NIDS Task 3 (1): Create WactionStores and Alerts

- Feed monitor stream into WactionStore



FeedIPsum

QUERY

```
select * from IPSumStream
```

NIDS Task 3 (1): Create WactionStores and Alerts

- Monitor No. of network flows and anomalies
- Feed stream into WactionStore



 **allFlowSummary**

QUERY

```
select datetime, total, anomalyNum from alertStream
```

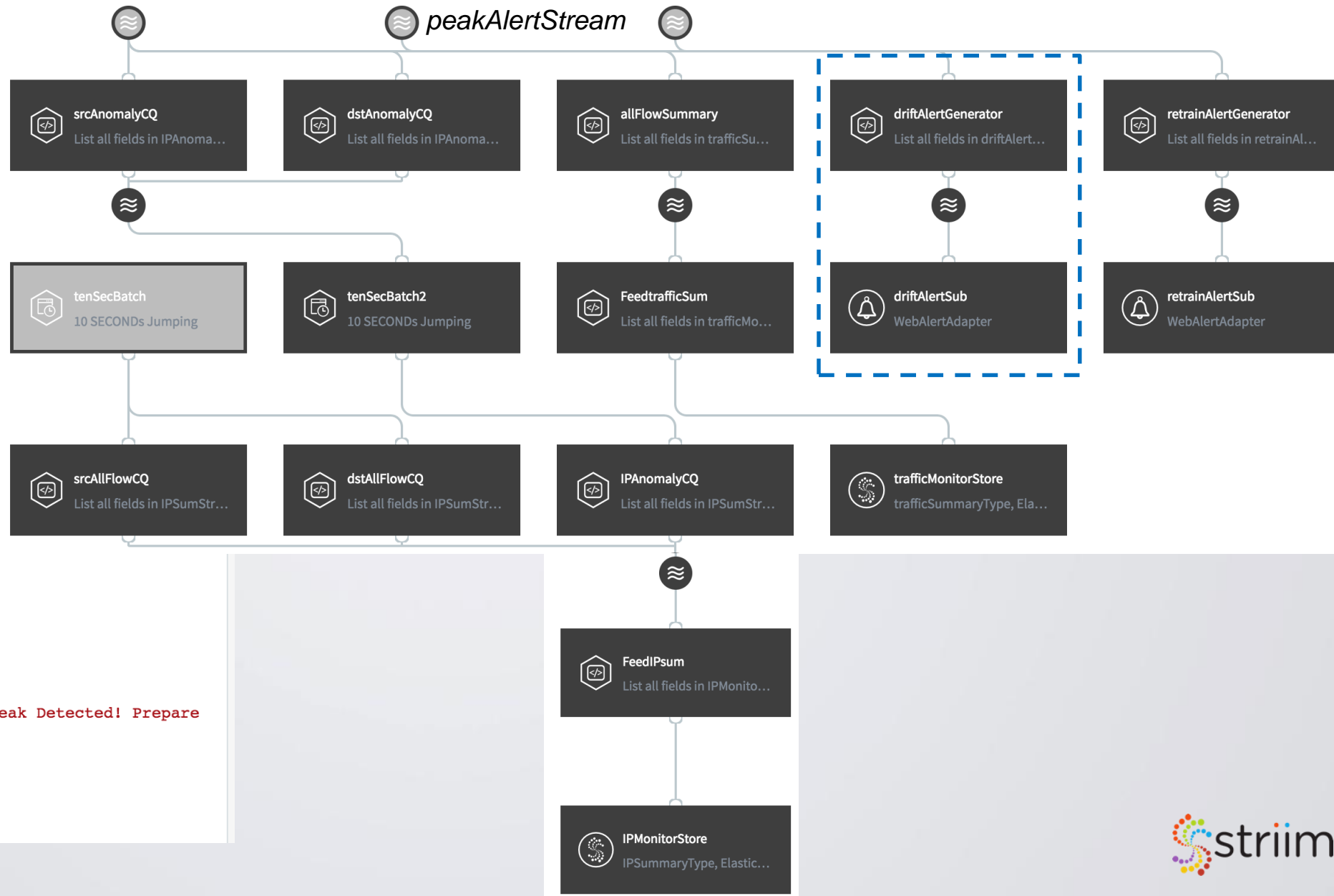
NIDS Task 3 (1): Create WactionStores and Alerts

- Alert on data pattern change

driftAlertGenerator

QUERY

```
SELECT 'Data Drift', s.name,  
CASE  
  WHEN s.anomalyPeak < 1 THEN 'info'  
  ELSE 'warning' END,  
CASE  
  WHEN s.anomalyPeak < 1 THEN 'cancel'  
  ELSE 'raise' END,  
CASE  
  WHEN s.anomalyPeak > 0 THEN 'Anomaly Peak Detected! Prepare  
to retrain the model!'  
  ELSE ''  
  END  
FROM peakAlertStream s
```



NIDS Task 3 (1): Create WactionStores and Alerts

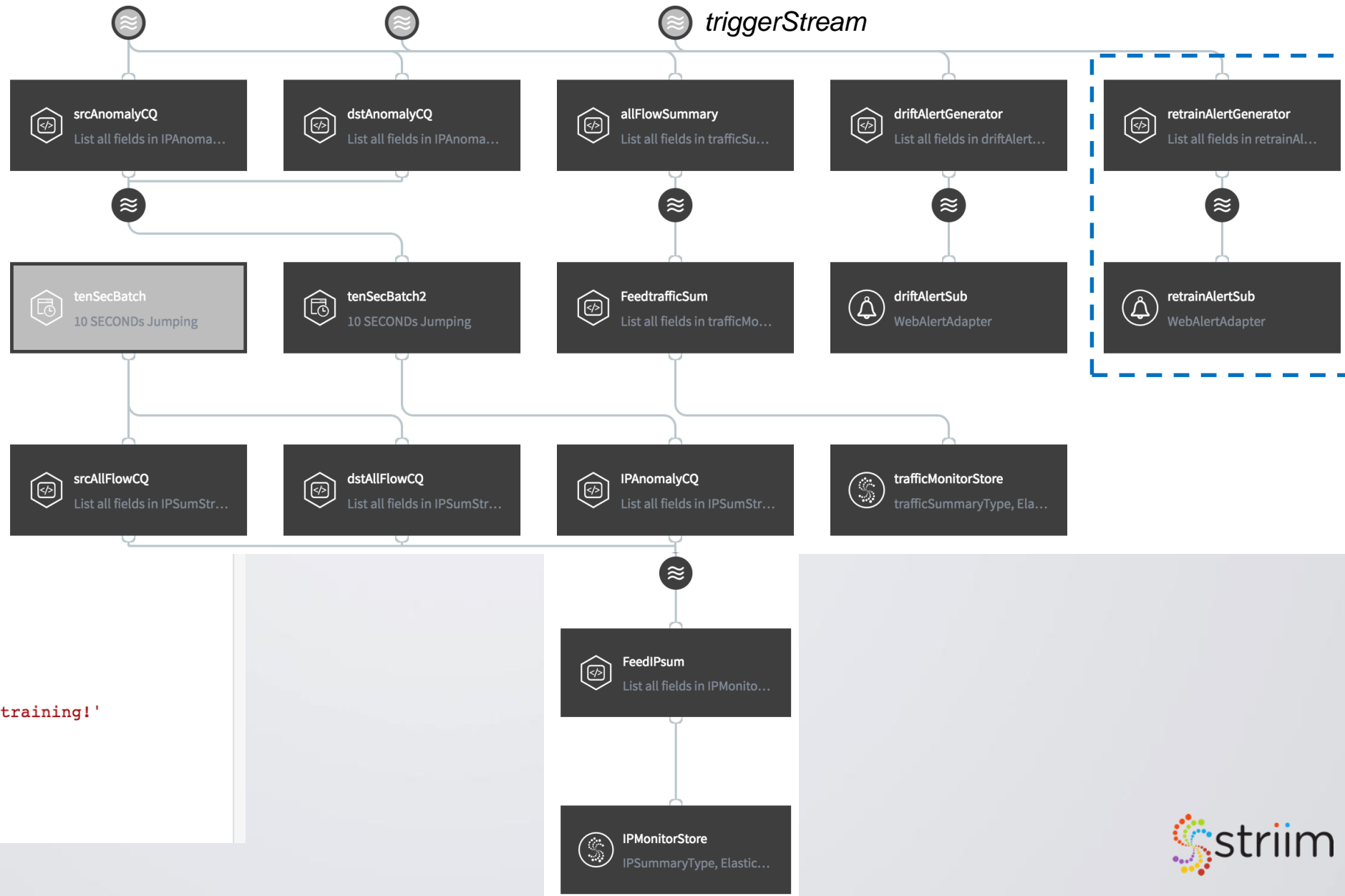
- Alert on retraining



retrainAlertGenerator

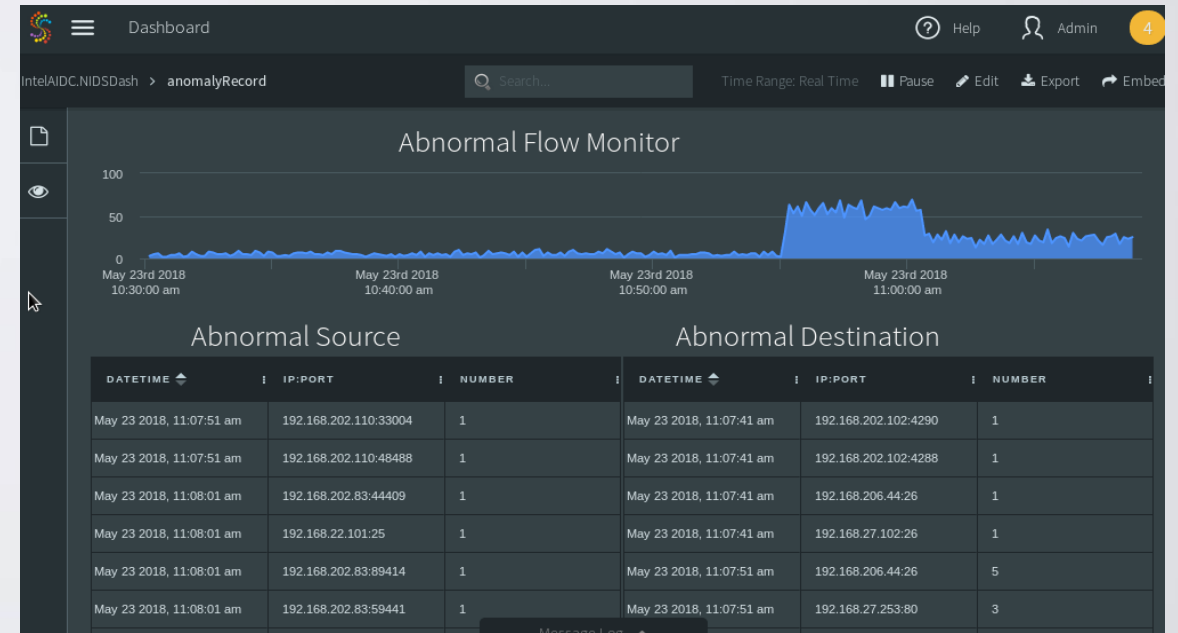
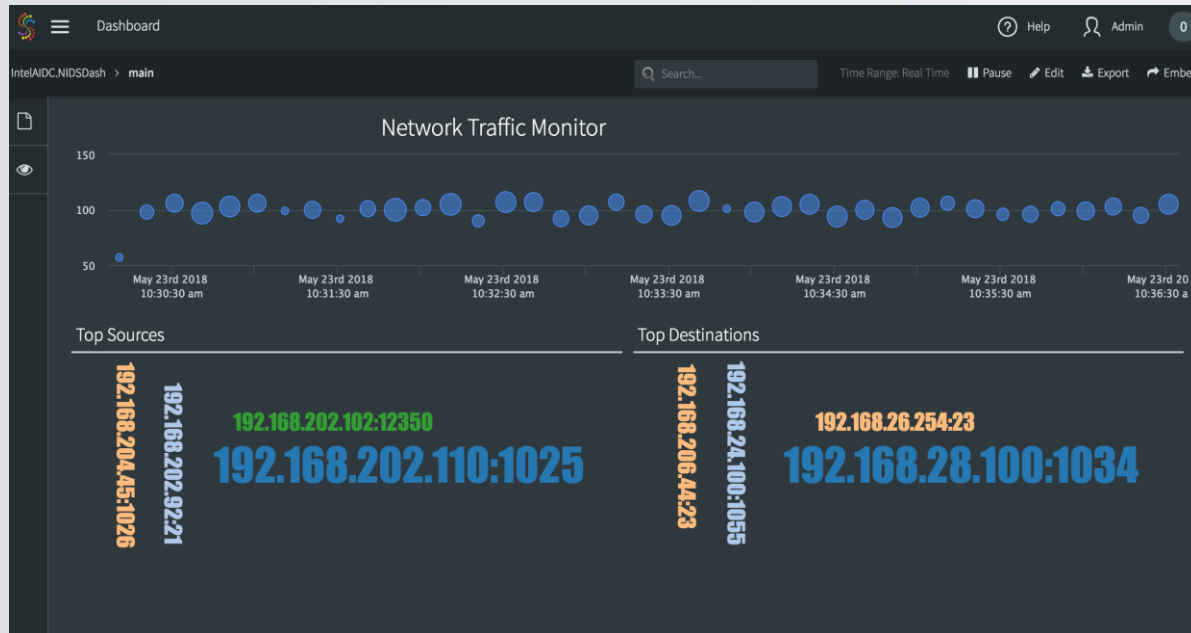
QUERY

```
SELECT 'Retrain', s.name,  
CASE  
  WHEN s.flag1+s.flag2 < 1 THEN 'info'  
  ELSE 'warning' END,  
CASE  
  WHEN s.flag1+s.flag2 < 1 THEN 'cancel'  
  ELSE 'raise' END,  
CASE  
  WHEN s.flag1+s.flag2 > 0 THEN 'Model retraining!'  
  ELSE ''  
END  
FROM triggerStream s
```



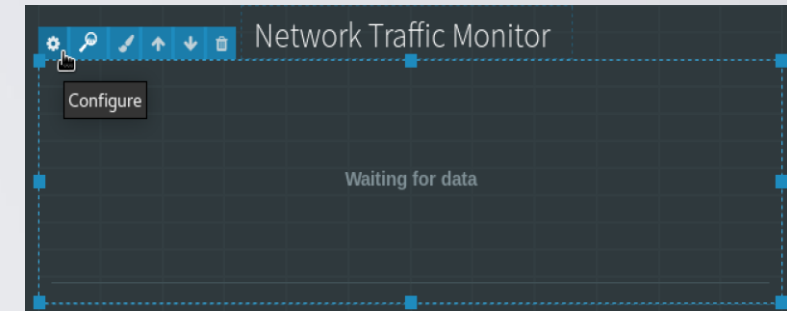
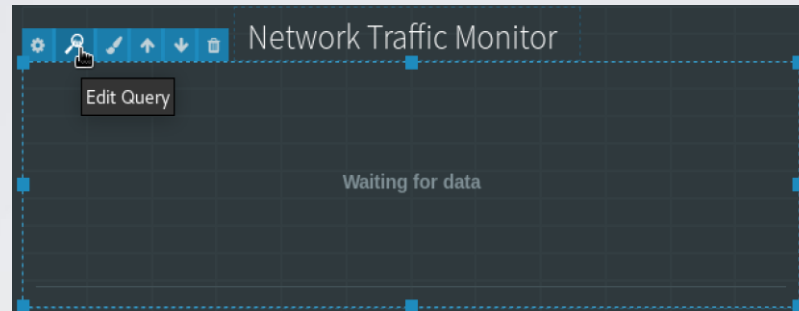
NIDS Task 3 (2): Build Dashboard

1. Start applications *monitor*, then *retrain*, then *anomalyDetection*
2. Navigate to Dashboard and view NIDSDash to see real-time visualization
3. Click “Network Traffic Monitor” on the main page to drill down and to see anomaly details



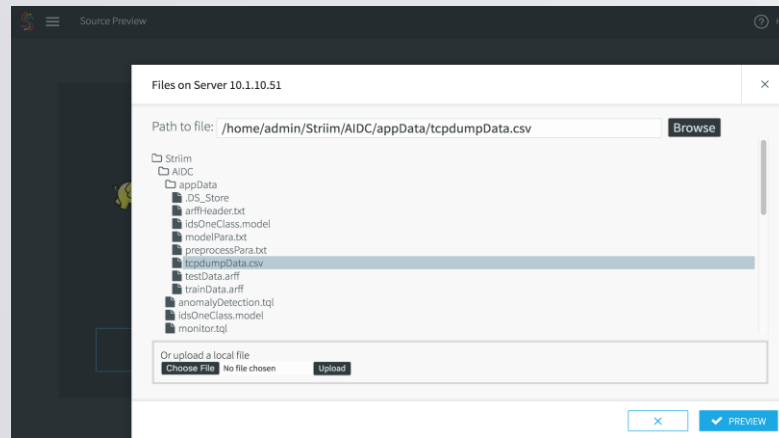
Learn More About Striim Product

Click *Edit* on the top right corner of dashboard to see how to configure a visualization chart.

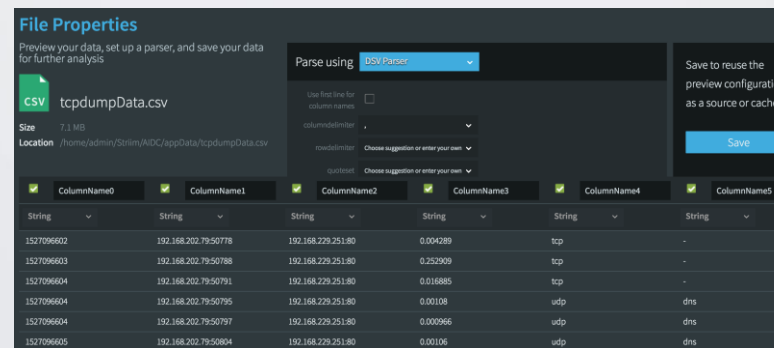


Open a new tab

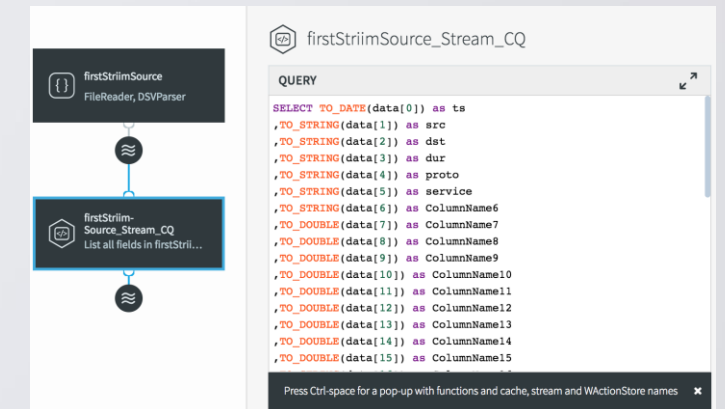
1. Go to Source Preview -> Browse -> choose tcpdumpData.csv to preview



2. Set columndelimiter as “,”, configure column name and type, save as source



3. Set application name as “firstStriimApp”, and source name as “firstStriimSource”



4. Edit a continuous query with SQL-like language, deploy your application and run to see output.



Key Takeaways

Streaming integration paves the way to ML operationalization

Striim provides reliable and efficient streaming integration solution

Support fast-track ML operationalization

Striim filters, enriches and prepares streaming data

Striim lands data continuously for model training

Striim supports continuous model serving on data streams

Striim handles model lifecycles with high automation

Striim visualizes the real-time data and predictions, and alerts on issues