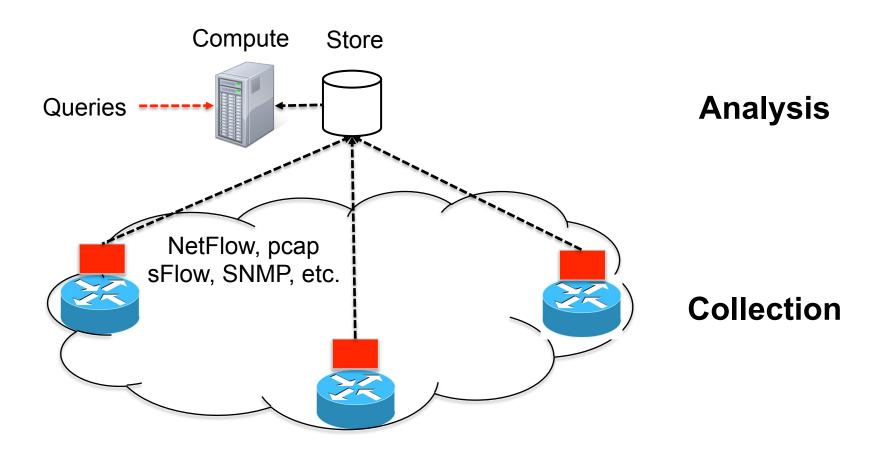
SONATA: Scalable Streaming Analytics for Network Telemetry

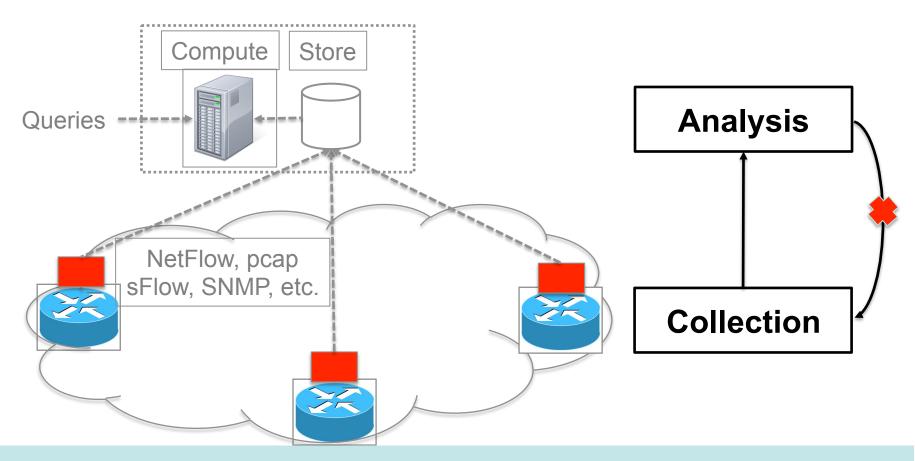
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Conventional Network Telemetry



Conventional Network Telemetry



Collection is **not** driven by Analysis

Problems with Status Quo

Expressibility

- Configure collection & analysis stages separately
- Static (and often coarse) data collection
- Brittle analysis setup---specific to collection tools

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- Expressibility
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Scalability

As Traffic Volume or # Monitoring Queries increases

Hard to answer queries in real-time

Hard to **express** & **scale** queries for network telemetry tasks!

SONATA: Query-Driven Telemetry

- Idea 1: Uniform Programming Abstraction
 Express queries as dataflow operations over pkt. tuples
- Idea 2: Query Partitioning
 Execute subset of dataflow operations in data plane
- Idea 3: Iterative Refinement

Iteratively zoom-in on traffic of interests

Makes it easier to **express** and **scale** network telemetry tasks!

Idea 1: Uniform Prog. Abstraction

Extensible Packet-tuple Abstraction

Queries operate over all packet tuples, at every location in the network

Expressive Dataflow Operators

- Most telemetry applications require
 - collecting aggregate statistics over subset of traffic
 - joining results of one analysis with the other
- Easy to express them as declarative queries composed of dataflow operators

Example Queries

Detecting Traffic Anomalies

Detect hosts for which # of unique source IPs sending DNS response messages exceeds threshold (Th)

```
pvictimIPs = pktStream(W)
    .filter(p => p.srcPort == 53)
    .map(p => (p.dstIP, p.srcIP))
    .distinct()
    .map((dstIP, srcIP) => (dstIP, 1))
```

Express queries without worrying about where and how they get executed

Example Queries

Confirming Reflection Attacks

Detect hosts with traffic anomalies that are of type RRSIG

```
victimIPs(t) = pktStream(W)
    .filter(p => p.srcPort == 53)
    .join(pVictimIPs(t), key='dstIP')
    .filter(p => p.dns.rr.type == RRSIG)
    .map(p => (p.dstIP, 1))
```

Join different packet tuple streams

```
.map((dstIP, count) => dstIP)
```

Changing Status Quo

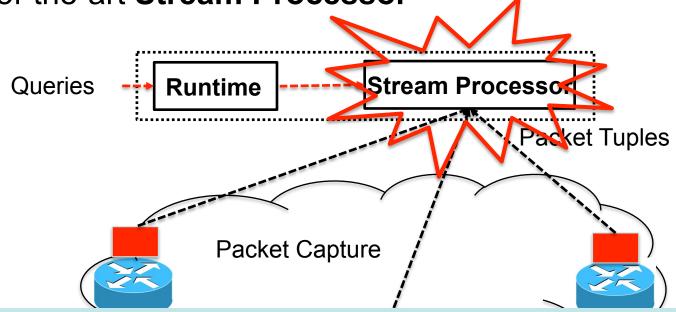
Expressibility

- Express dataflow queries over packet tuples
- Not tied to low-level (3rd party/platform-specific) APIs
- Trivial to add new queries and change collection tools

Easier to express network telemetry tasks!

Query ExecutionUse Scalable Stream Processors

Process all (or subset of) captured packet tuples using state-of-the-art **Stream Processor**



Expressible but not Scalable!

Scalable Query Execution

Query Partitioning

- Execute subset of dataflow operators in data plane
- Reduce packet tuples at the cost of additional state in the data plane

Iterative Refinement

- Iteratively zoom-in on traffic of interests
- Reduce state at the cost of additional detection delay

Idea 2: Query Partitioning

Observation

Data Plane can process packets at line rate

- How it works? Dataflow operations in data plane,
 - filter, sample operations for OF-based data plane
 - map, reduce, filter, join, sample operations for PISAbased data plane

Trade-off

Trades packet processing cost with additional state in the data plane

PISA Targets for Query Partitioning

- Programmable parsing
 Allow new query-specific header fields for parsing
- State in packets & registers
 Support simple stateful computations
- Customizable hash functions
 Support hash functions over flexible set of fields
- Flexible match/action table pipelines
 Support match/action tables with prog. actions

Compiling Dataflow Operators

Map, Filter & Sample

Apply sequence of match-action tables

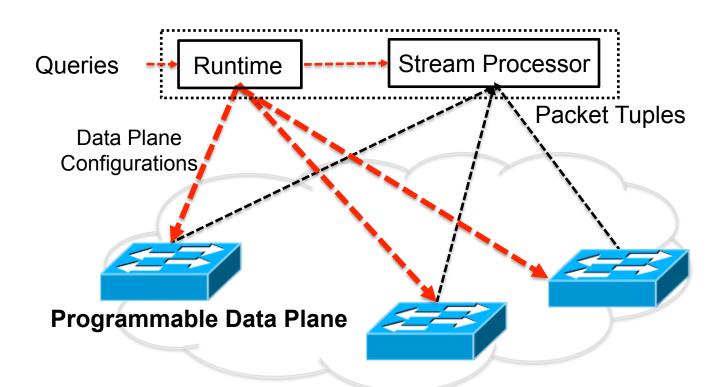
Distinct & Reduce

- Compute index, & read value from hash tables
- Apply function (e.g., bit_or for distinct) & then update the hash table
- Use sketches, e.g. reduce(sum) → CM Sketches

Limitations

Complex transformations, e.g. log, regex, etc.

Query Partitioning in Action



Runtime Partitions Input Queries

Idea 3: Iterative Refinement

Observation

Small fraction of traffic satisfies monitoring queries

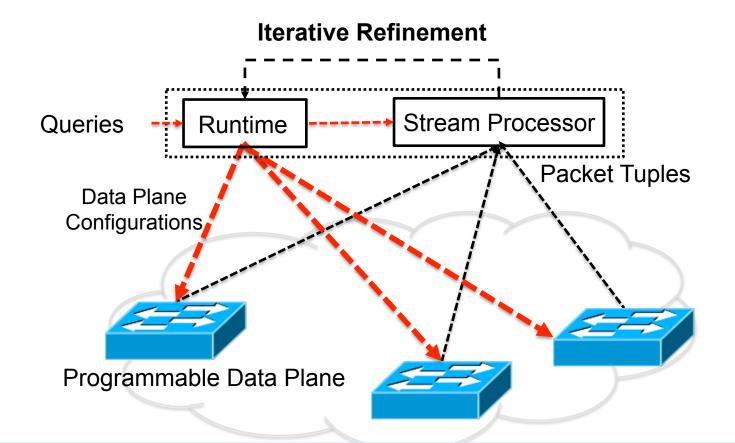
How it works

- Augment operators' query to observe at coarser level
- Iteratively (over successive window intervals) zoom-in to filter out uninteresting traffic

Trade-offs

- Reduces packet processing & data plane state cost
- Introduces additional detection delay cost

Iterative Refinement in Action



Collection is now driven by Analysis!

Scalable Query Execution

Query Partitioning

- Execute subset of dataflow operators in data plane
- Reduce packet tuples at the cost of additional state in the data plane

Iterative Refinement

- Iteratively zoom-in on traffic of interests
- Reduce state at the cost of additional detection delay

How to select the best query plan?

Query Planning

Traffic Anomaly Query

Partitioning Plans

Plan 1: Data Plane only

Plan 2: Stream Processor only

```
pktStream(W)
.filter(p => p.srcPort == 53)
.map(p => (p.dstIP, p.srcIP))
.distinct()
.map((dstIP, srcIP)=>(dstIP,1))
.reduceByKey(sum)
.filter((dstIP,count)=>count>Th)
.map((dstIP, count) => dstIP)
```

Refinement Plans

- Refinement key: dstIP
- Refinement levels: {/8, /32}

Query Planning

Traffic Anomaly Query

Partitioning Plans

Plan 1: Data Plane only

Plan 2: Stream Processor only

Refinement Plans

- Refinement key: dstIP

Refinement levels: {/8, /32}

Query Plan Graph

Src

W_{0,32,2}

W_{0,32,1}

dIP/32,1

dIP/8,2

dIP/8,1

 $W_{8,32,2}$

dIP/32,2

 $W_{8,32,1}$

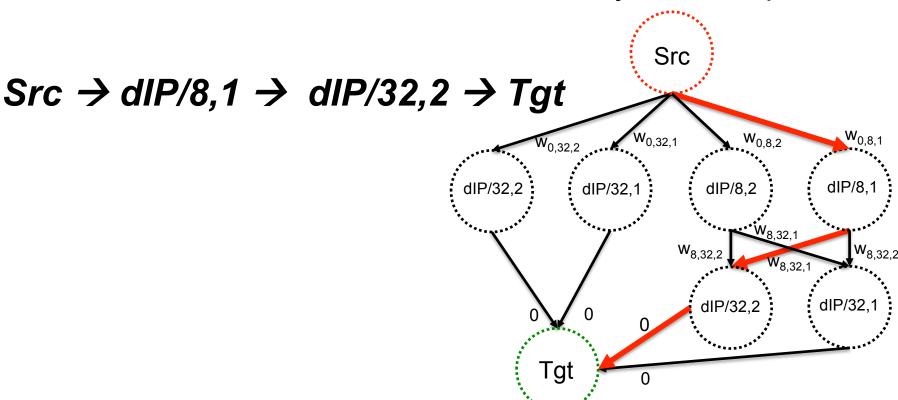
dIP/32,1

dIP/32,2

Tgt

Query Planning

Query Plan Graph



Selects plan with smallest weighted cost

SONATAQuery-Driven Network Telemetry

Application Interface

Express queries w/o worrying about **where** and **how** they will be executed

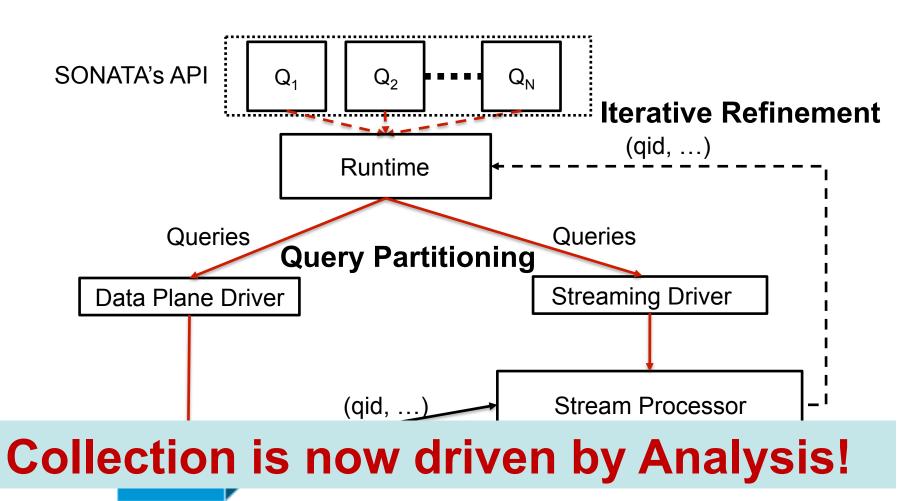
Runtime System

Iteratively refines and partitions each input query

Data Plane & Streaming Drivers

Compile input queries to target-specific configurations/ queries

Implementation



Evaluation

Workload

Large-IXP network: 2 hours long IPFIX trace, 3 Tbps peak traffic, packet sampling rate = 1/10K

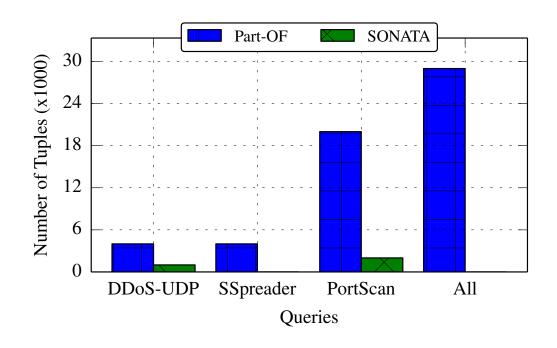
Queries

DDoS-UDP, SSpreader, PortScan

Comparisons

Part-OF, Part-PISA, Fixed-Refinement

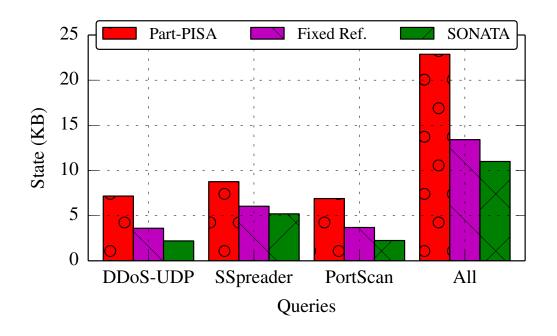
Benefits of Query Partitioning



Number of pkt tuples processed by Stream Processor

Executing stateful operations in data plane reduces workload on Stream Proc.

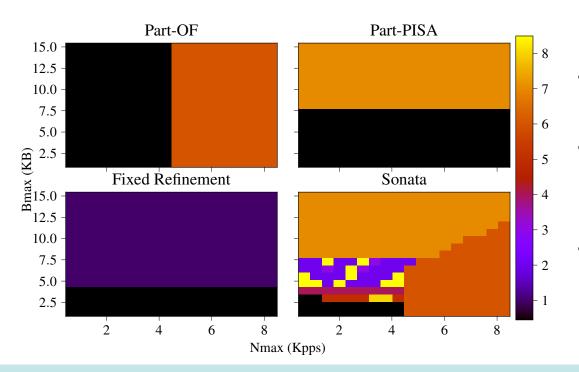
Benefits of Iterative refinement



State (KB) required by data plane targets

Iterative refinement reduces state required by the data plane targets

Benefits of Query Planning



- B_{max}: Max. state data plane can support
- N_{max}: Max. pkt. tuples stream processor can process
- Each color represents a unique query plan

SONATA makes best use of available resources

Changing Status Quo

- Expressibility
 - Express Dataflow queries over packet tuples
 - Not worry about how and where the query is executed
 - Adding new queries and collection tools is trivial
- Scalability
 - Answers hundreds of queries in real-time for traffic volume as high as few Tb/s

Expressible & Scalable!

- · tupies processed by the stream processor
- state in the data plane

Summary

- SONATA makes it easier to express and scale network telemetry tasks using
 - Uniform Programming Abstraction
 - Query Partitioning
 - Iterative Refinement

- Running Code
 - Github: github.com/Sonata-Princeton/SONATA-DEV
 - Run test queries or express new ones

sonata.cs.princeton.edu