Uncertainty-Aware Event Analytics over Distributed Settings

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(Geo) Distributed Architectures

- ~30 B connected devices by 2022 [Cisco VNI '18]
- Several data generation technologies
 - Smart Cities, Smart Grids, Smart Houses
 - Industry 4.0, Smart Factories

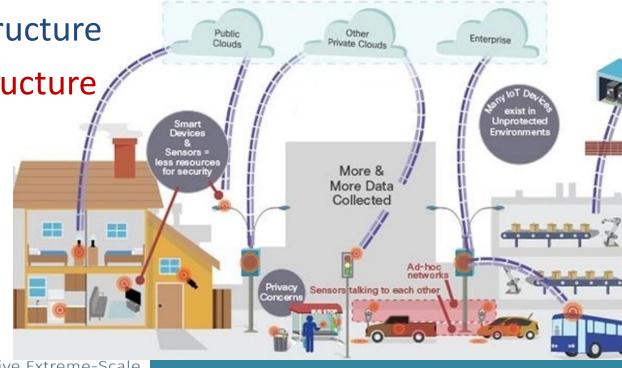
Telecom Infrastructure

Banking Infrastructure

Social Networks

Wearables

• ...



Big (Event) Data Challenges: 1-D B4 4-Vs

- Distribution: Massively distributed data streams →
 Need to reduce communication
- Volume

NETWORK BOUND

- Velocity [e.g. Zleiter & Risch, PVLDB 2011, Karimov et al, ICDE 2018]
- Veracity (Uncertainty):
 - Imprecise Attribute Values, Uncertain Event Occurrence
 - Rules applied at a certain level of confidence
 - Event Forecasting, Approximation
- Variety: various devices produce diverse data formats

E. Zeitler and T. Risch. Massive scale-out of expensive continuous queries. PVLDB, 4(11):1181–1188, 2011. J. Karimov et al. Benchmarking Distributed Stream Data Processing Systems. ICDE, 1507-1518, 2018



Big (Event) Data Challenges: 1-D B4 4-Vs

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This Work: Handling Distribution + Uncertainty →

Boost manageable Volume and Velocity →

Extract Value (Event Analytics) out of Big Event Data





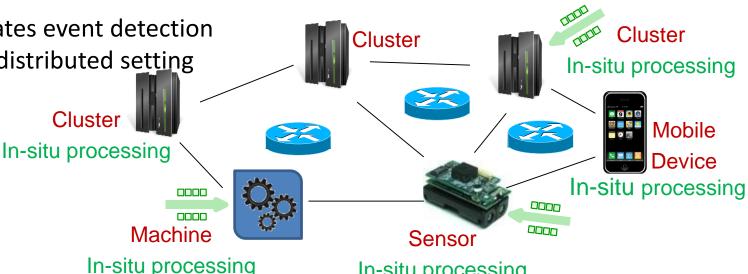
Our Contributions

Generic Tools for Scalable Event-Analytics

- Tool 1: In-situ Processing
 - In-situ filter installation "safely" avoids communication
- **Tool 2: Monitoring Protocol**
 - Incorporates in-situ filters
 - Orchestrates event detection over the distributed setting

Integration in the FERARI **Platform Prototype**

- I. Flouris et al. FERARI: A Prototype for Complex Event Processing over Streaming Multi-cloud Platforms. SIGMOD, 2093-2096, 2016.
- I. Flouris et al. Complex event processing over streaming multi-cloud platforms: the FERARI approach. DEBS, 348-349, 2016





What Kind of Event-Analytics?

Event Data

- CEs: Complex Event Patterns
 - AGGRegation (Thresholded)
 - SUM, COUNT, AVG etc
 - lying <u>above/below</u> Threshold T
 - NON_AGGRegative Operator
 - AND: Logical Conjunction
 - OR: Logical Disjunction
 - SEQ: Time-ordered Conjunction
- (Un)Certainty/Confidence
 Threshold C
- SDEs: Simple Derived Events
 - Updates on AGGR_i

Target Queries/CE Detection

```
PATTERN NON_AGGR  (AGGR_1 > T_1, \\ ..., \\ AGGR_m > T_m) Q \\ [WHERE conditions] \\ [PARTITION BY key] \\ [HAVING Q.Certainty> C \\ WITHIN window const
```



Case Study: Mobile Fraud Detection

Q₁: FrequentToVoIPCalls

PATTERN (COUNT (CDR) > T) Q_1

WHERE CDR.prefix = VoIP

PARTITION BY CDR.callerID

HAVING Q_1 .Certainty > C

WITHIN Y minutes

CDR = Call Detail Record

SDE Stream

caller callee call start time duration p

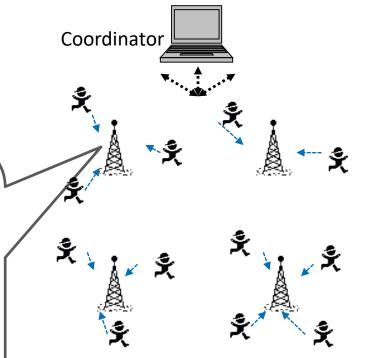
62	23	11:10:23 05 - 10	22	0,41
38	45	11:10:24 05 - 10	21	0,43
34	22	11:10:23 05 - 10	13	0,41
83	19	11:10:25 05 - 10	6	0,42
10	22	11:10:24 05 – 10	6	0,4
34	41	11:10:24 05 - 10	9	0,41

Each VoIP call fraudulent with probability p

2-tiered Architecture

Coordinator – Query Source

N sites - antennas





Antenna Sites
Smartphone Users Commute
Call Status updates



Uncertainty-Aware In-situ Filters

Basic Concept: Suppress communication if no CEs can be produced

- Random Variable (R.V.) X ≡ AGGR ∈ {COUNT, SUM, ...}
- Global Filter @ Coordinator

$$1-CDF[X,T]=P[X > T] \leq C$$

- In-situ Filters @ each site A_i (N antennas), R.V. $X_i \equiv AGGR_i$
 - If $X = \sum X_i \rightarrow$

$$CDF_{i}[X_{i}, T/N] \ge \sqrt[N]{1-C}$$

• If $X = \prod X_i \rightarrow$

$$CDF_{i}[X_{i}, \sqrt[N]{T}] \ge \sqrt[N]{1-C}$$

Decomposable Probability Distributions						
Distribution	PDF	Remarks	Decomposition Example	In-situ Filter for 1 - CDF(X, T) > C		
Normal	$\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(x-\mu)^2}{2\sigma^2}},$	$\forall x \in \mathbb{R}$	$X_{l} \sim Normal(\mu_{l}, \sigma_{l}^{2})$ $X = \sum_{l=1}^{N} X_{l} \sim Normal(\sum_{l=1}^{N} \mu_{l}, \sum_{l=1}^{N} \sigma_{l}^{2})$	$\sqrt[N]{1-C} \le CDF(X_l, \frac{T}{N})$		
Log-Normal	$\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}},$	$\forall x > 0$ $\mu \in \mathbb{R}(\neq \text{mean})$ $\sigma > 0 (\neq \text{st.dev.})$	$X_{l} \sim LogNormal(\mu_{l}, \sigma_{l}^{2})$ $X = \prod_{l=1}^{N} X_{l} \sim LogNormal(\sum_{l=1}^{N} \mu_{l}, \sum_{l=1}^{N} \sigma_{l}^{2})$	$\sqrt[N]{1-C} \le CDF(X_l, \sqrt[N]{T})$		
Chi-Square	$\frac{1}{2^{\nu/2}\Gamma\left(\frac{\nu}{2}\right)}x^{\frac{\nu}{2}-1}e^{-\frac{x}{2}}$	$\forall x > 0$ $v \in \mathbb{N}^+$ degrees of freedom	$X_{l} \sim x^{2}(v_{l})$ $X = \sum_{l=1}^{N} X_{l} \sim x^{2}(\sum_{l=1}^{N} v_{l})$	$ \frac{\sqrt[N]{1-C}}{\sqrt[N]{1-C}} \leq CDF(X_{l}, \frac{T}{N}) $		
Cauchy	$\frac{1}{\pi s \left[1 + \left(\frac{x - y}{s}\right)^2\right]}$	$\forall x \in \mathbb{R}$ $v \in \mathbb{R}(\text{location})$ s > 0 (scale)	$X_{l} \sim Cauchy(v_{l}, s_{l})$ $X = \sum_{i=1}^{N} X_{i} \sim Cauchy(\sum_{i=1}^{N} v_{i}, \sum_{i=1}^{N} s_{i})$	$V_{1-C} \le CDF(X_{l}, \frac{T}{N})$		
Poisson	$\frac{\lambda^{x}e^{-\lambda}}{x!}$	$\forall x \in \mathbb{N}$ $\lambda > 0$	$X_{l} \sim Poisson(\lambda_{l})$ $X = \sum_{l=1}^{N} X_{l} \sim Poisson(\sum_{l=1}^{N} \lambda_{l})$	$ \frac{\sqrt[N]{1-C}}{CDF(X_{I}, \frac{T}{N})} $		
Gamma	$\frac{1}{\Gamma(\alpha)\theta^{\alpha}} x^{\alpha-1} e^{-\frac{x}{\alpha}}$	$\forall x > 0$ $\alpha > 0 \text{(shape)}$ $\theta > 0 \text{ (scale)}$	$X_{l} \sim Gamma(\alpha_{l}, \theta)$ $X = \sum_{l=1}^{N} X_{l} \sim Gamma(\sum_{l=1}^{N} \alpha_{l}, \theta)$	$\sqrt[N]{1-C} \le CDF(X_l, \frac{T}{N})$		
	_ <u>x-v</u>	$\forall x \in \mathbb{R}$	$X_l \sim Logistic(v_l, s_l)$ (approx.)	<u>₩1 – C</u> <		

 $v \in \mathbb{R}(\text{location})$

s > 0 (scale)

 $\forall x > 0$

 $\lambda > 0$ (rate)

x = 0, 1, ..., n

 $p \in [0, 1]$

 $n \in \mathbb{N}$

Logistic

Exponential

Binomial

 $\lambda e^{-\lambda x}$

 $\binom{n}{x} p^{x} (1 - p)^{n-x}$

 $X = \sum_{i=1}^{N} X_i \sim Logistic(\sum_{i=1}^{N} v_i, \sqrt{\sum_{i=1}^{N} s_i^2})$

 $X_i \sim Gamma(\frac{u_i}{N}, \frac{1}{\lambda})$

 $X = {\textstyle\sum\limits_{}^{N}} X_{l} \sim Exp(\lambda)$

 $X_l \sim Binomial(n_l, p)$

 $X = \sum X_l \sim Binomial(\sum n_l, p)$

 $\sqrt[N]{1-C} \le$

 $CDF(X_l, \frac{\overline{T}}{N})$

 $\sqrt[N]{1-C} \le$

 $CDF(X_l, \frac{T}{N})$

 $\sqrt[N]{1-C} \le$

 $CDF(X_l, \frac{T}{N})$

$$\text{Normal} \quad \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \qquad \forall x \in \mathbb{R} \quad \begin{array}{c} X_l \sim Normal(\mu_l, \sigma_l^2) \\ X = \sum\limits_{l=1}^N X_l \sim Normal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \sum\limits_{l=1}^N X_l \sim Normal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \sum\limits_{l=1}^N X_l \sim LogNormal(\mu_l, \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \sigma_l^2) \\ X = \prod\limits_{l=1}^N X_l \sim LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l > LogNormal(\sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l, \sum\limits_{l=1}^N \mu_l$$

Case Study: Mobile Fraud Detection

Q₁: FrequentToVoIPCalls

```
\label{eq:pattern} \begin{array}{lll} \text{PATTERN}\left(\text{COUNT} & (\text{CDR}) > T\right) & \mathbb{Q}_1 \\ \\ \text{WHERE CDR.prefix} &= \text{VoIP} \\ \\ \text{PARTITION BY CDR.callerID} & \textbf{CDR} &= \textbf{Call Detail Record} \\ \\ \text{HAVING } \mathbb{Q}_1.\text{Certainty} &> \mathbb{C} \\ \\ \text{WITHIN Y minutes} \end{array}
```

- Each VoIP call fraudulent with probability p ~ Bernoulli[p]
- n_i calls @ A_i , $n = \sum n_i$ total calls for a subscriber, $X = \sum X_i$
- $X_i = COUNT_i \sim Binomial[n_i, p] \rightarrow X = COUNT \sim Binomial[n, p]$
- Global Filter @ Coordinator

$$1-CDF_{Binomial}[X,T] \leq C$$

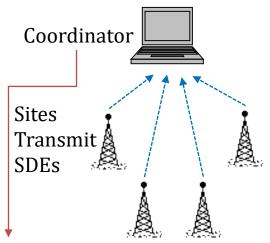
In-situ Filters @ each site A_i

$$CDF_{\text{Binomial}}[X_{i},T/N] \geq \sqrt[N]{1-C}$$



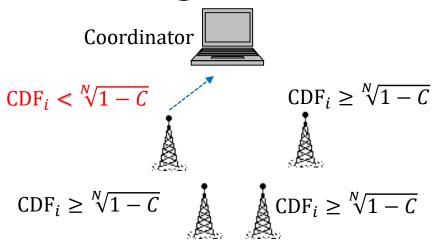
3-Phase Monitoring Protocol

Initialization Phase



- 1. Estimate PDF if not known in-hand
- 2. Set X~PDF(.)
- 3. Transmit $X_i \sim PDF(.)$ to each site A_i
- 4, Go to Monitoring Phase

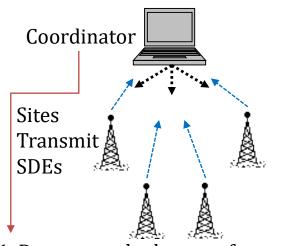
Monitoring Phase



$$CDF_i \ge \sqrt[N]{1 - C} \Rightarrow A_i$$
 caches relevant events $CDF_i < \sqrt[N]{1 - C} \Rightarrow A_i$ Synchronization Phase

3-Phase Monitoring Protocol

Synchronization Phase



Slack Allocation:

Adaptively increase or decrease the $\sqrt[N]{1-C}$ threshold for each site

- 1. Request cached events from sites $\{A_1, \dots, A_N\}$
- 2.1 SyncCase A when Pr[X > T] > C [Global Filter violated]:

2.1.1

Produce CEs, receive new events Go to 2.1

2.1.2

[Global Filter holds]

 $2.1.3 \text{ If } Pr[X > T] \le C$

Go to Initialization phase

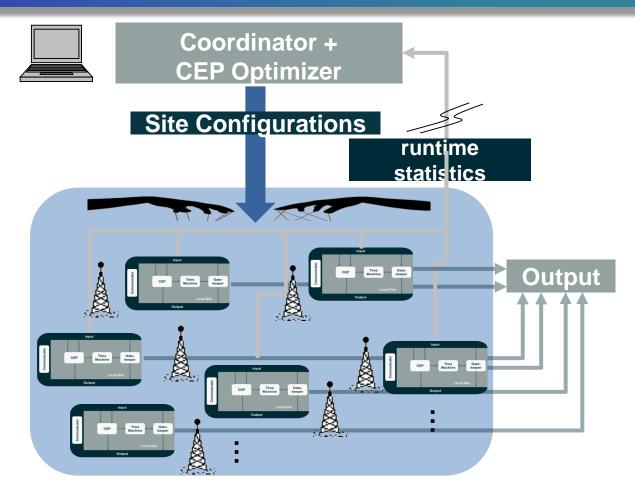
- 2.2 SyncCase B when $Pr[X > T] \le C$:
 - 2.2.1 Slack Allocation
 - 2.2.2 Go to Monitoring phase

Implementation in FERARI Platform

@ distributed architecture

FERARI Inter-site Orchestration





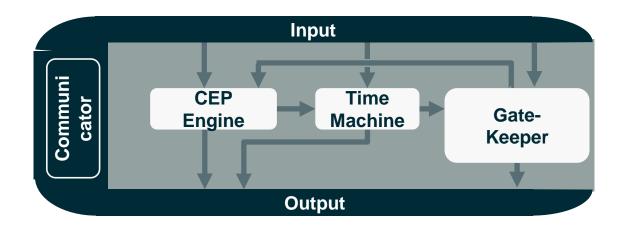
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Implementation in FERARI Platform

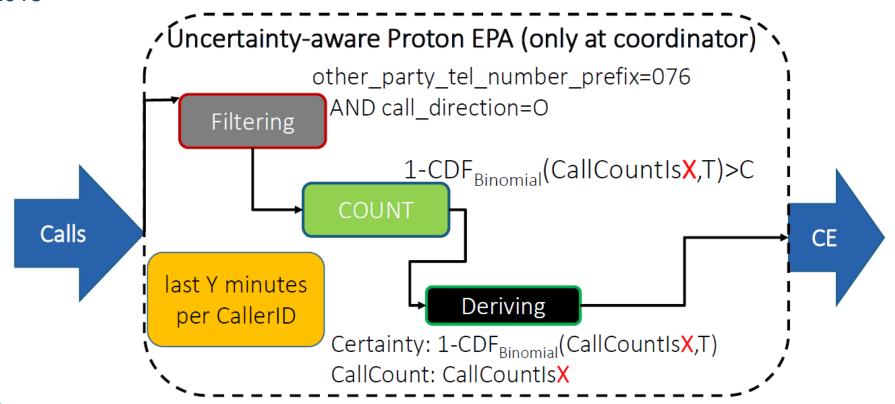
@ each site

- Each site runs an Apache Storm topology
- Support any CEP Engine
- Current Implementations
 - ProtonOnStorm IBM Haifa https://github.com/ishkin/Proton
 - Esper http://www.espertech.com/esper/
- Bridging the gap between two prototypes!



Traditional Implementation in Proton

- Only @ coordinator [Correia et al, DEBS 2015]
- No parallelism
- Naive central data collection at the coordinator
- I. Correia et al. The uncertain case of credit card fraud detection. DEBS, 181-192, 2015

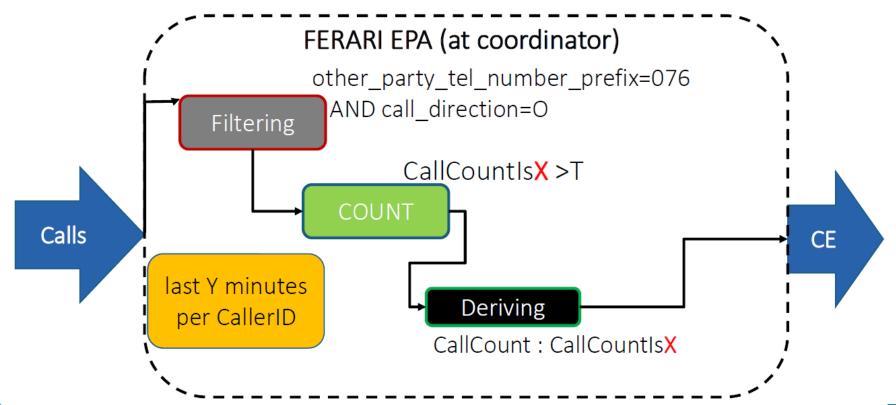




FERARI Implementation

@ coordinator

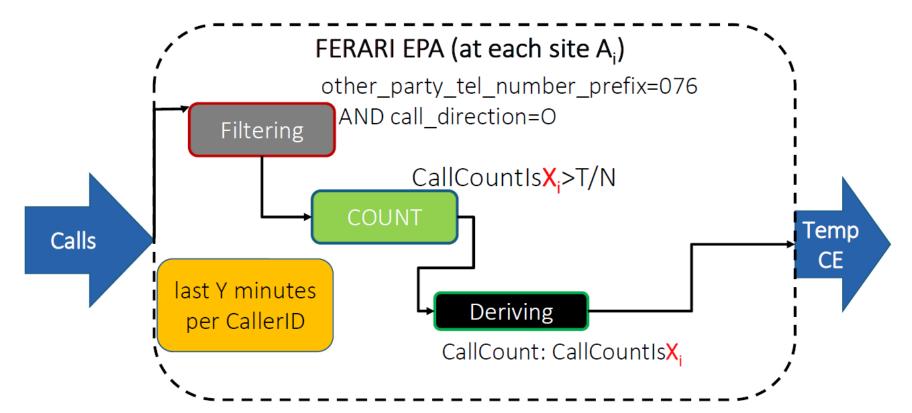
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- Monitoring protocol for network orchestration
- No support for uncertainty



FERARI Implementation

@ each site

- Parallel processing in Apache Storm
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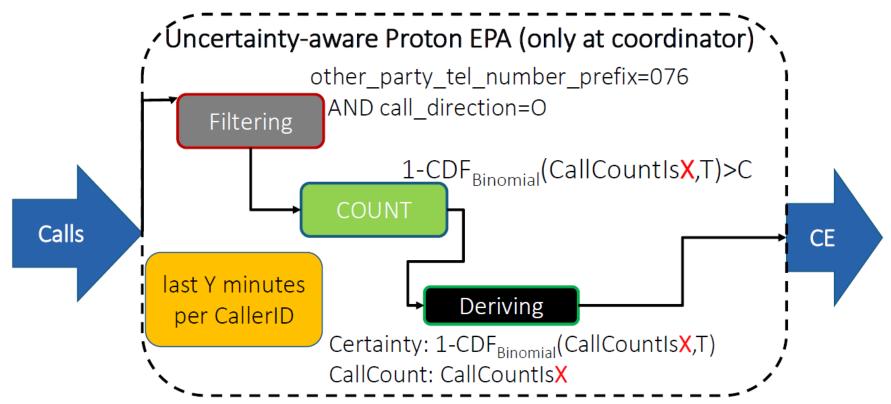




This Work: Uncertainty-aware FERARI

@ coordinator

- Parallel processing in Apache Storm
- Monitoring protocol for network orchestration
- Support for uncertainty

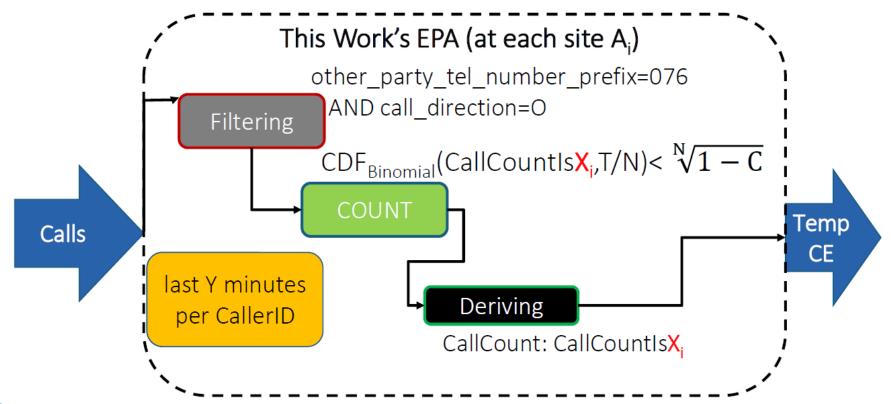




This Work: Uncertainty-aware FERARI

@ each site

- Parallel processing in Apache Storm
- Monitoring protocol for network orchestration
- Support for uncertainty





Evaluation Results

Experimental Setup

- 160M calls from
 [Flouris et al, SIGMOD 2016]
- N=3 to N=10
- C=0.9 to 0.5
- Competitors
 - This Work
 - FERARI + Uncertainty-Aware

Coordinator

 Naïve central data collection (omitted)

Highlights

- N=3, C=0,9→ An order of magnitude less transmitted messages
- On average 4 times less transmitted messages across various N and C
- N \rightarrow 10 or C \rightarrow 0.5 no earnings
 - Recall:

$$CDF_{i}[X_{i}, T/N] \geq \sqrt[N]{1-C}$$

- As N increases
 - $\sqrt[N]{1-C} \rightarrow 1$
 - $T/N \rightarrow 0$





Summary & Future Work

- Optimized distributed execution of uncertainty-aware event queries
- Communication Reduction
 - Construction and installation of In-situ Filters at sites
- Network Orchestration
 - Introduction of monitoring protocol
- Proof-of-Concept
 - Extending FERARI streaming multi-cloud platform
- Real case study from the telecom domain
- Future work:
 - Sampling among sites to increase performance
 - Loosen the uncertainty independence assumption



http://infore-project.eu/

Uncertainty-Aware Event Analytics over Distributed Settings

Thank you! Questions?

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