



# Intelligent SDN based Traffic (de)Aggregation and Measurement Paradigm (iSTAMP): Theory

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## Network Measurement

Direct and indirect network measurement techniques provide essential information for network design, network monitoring and management and network security

## Network Measurement: Limitations and Challenges

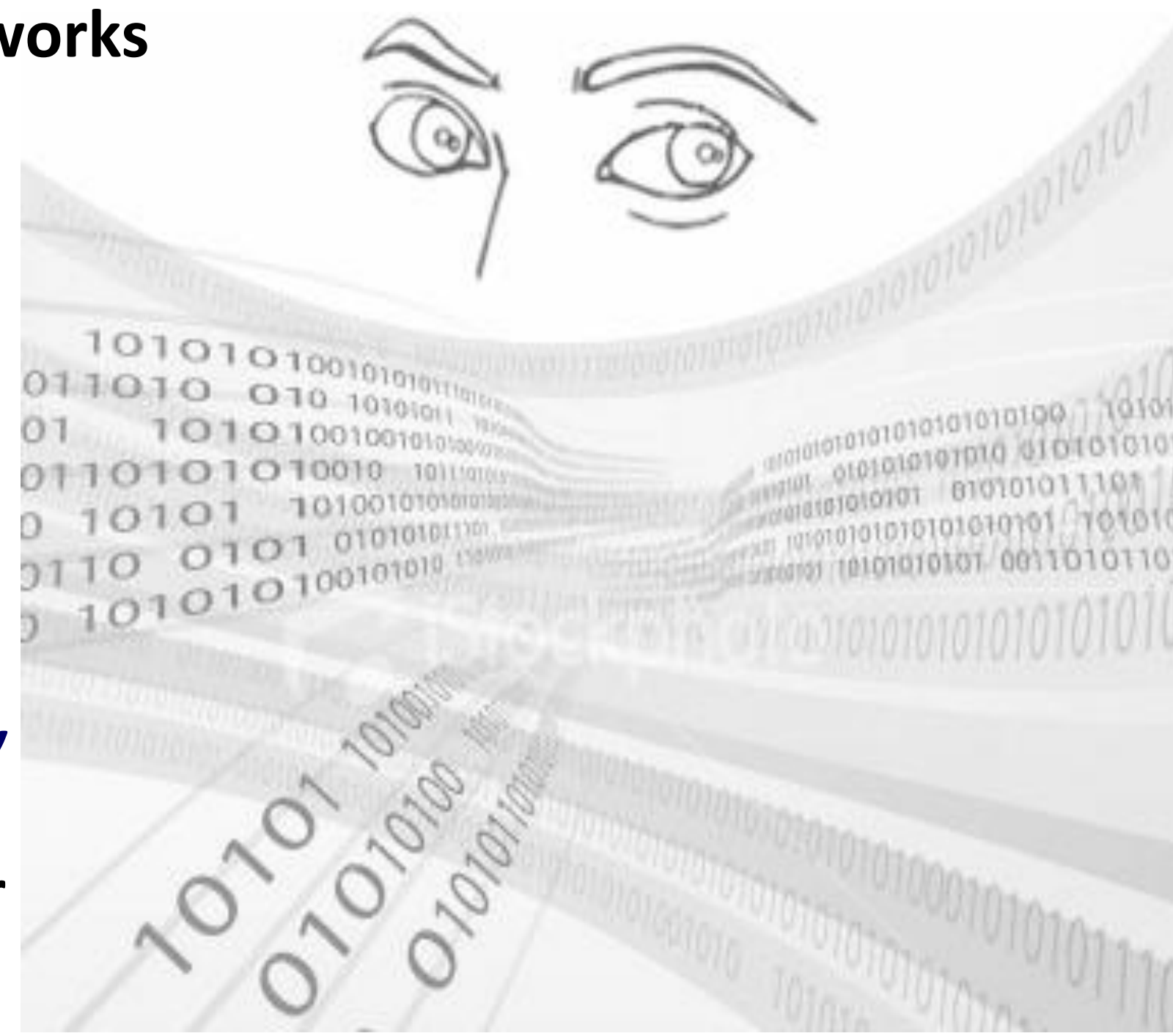
- Feasibility and Complexity of the measurement process
- Exploding Traffic Volume
- Limited Measurement and/or Processing Resources
- High computational complexity in large-scale networks
- Limited performance accuracy
- Sensitivity to noise and failures

## Solution

*Efficient and Intelligent Software Defined Network  
Measurement & Inference under Resource Constraints*

## where

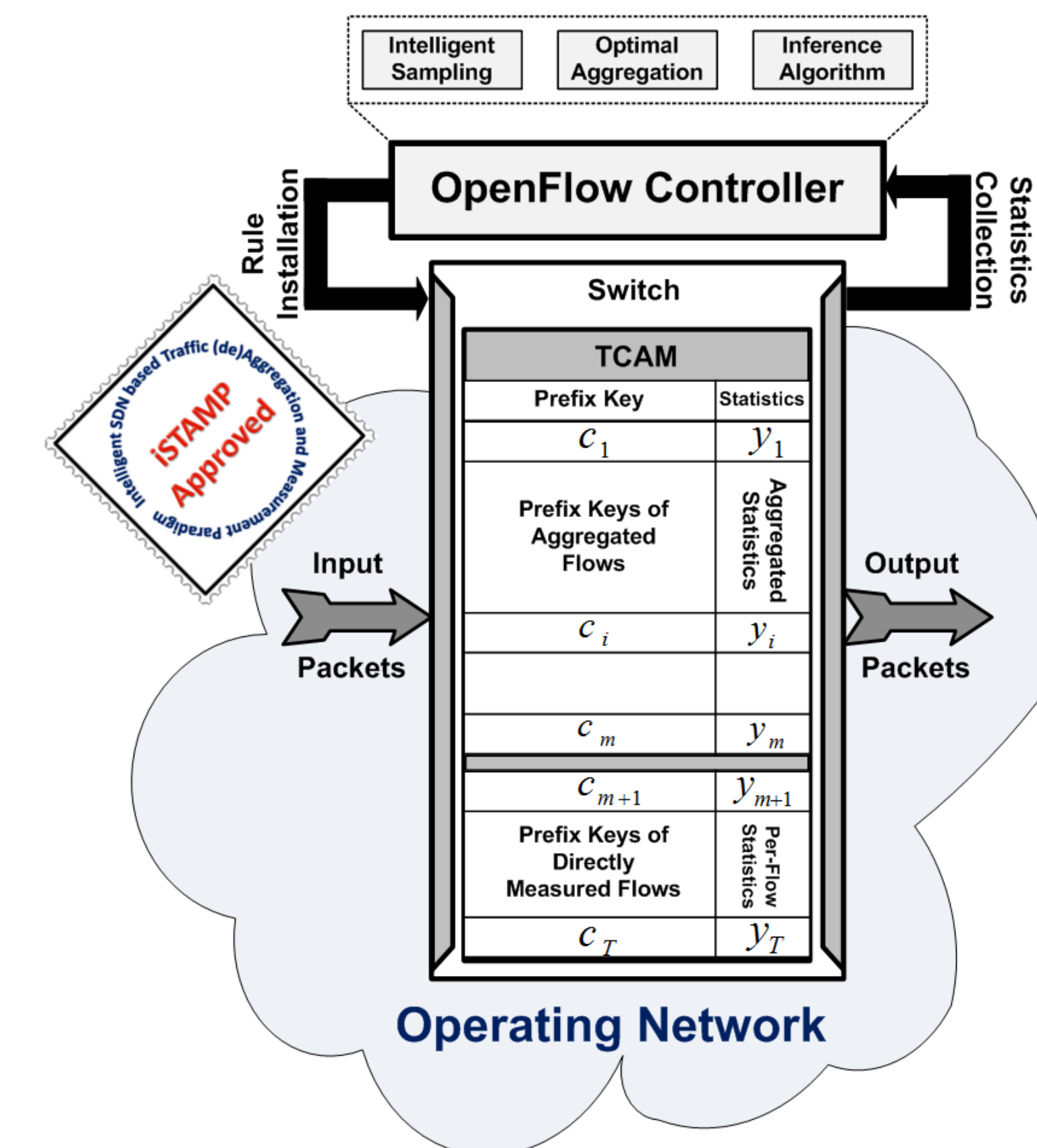
- Measurement Resources are *optimally & adaptively* allocated
- Powerful inference techniques are *efficiently* used for estimating the attribute of interests



## iSTAMP: Framework

iSTAMP leverages OpenFlow to dynamically partition the TCAM entries of a switch/router into two parts for optimal aggregation and direct flow sampling. iSTAMP has three main components:

- ❑ An Optimal aggregation technique to produce a **well-compressed** aggregated flow measurements that can lead to the **best estimation accuracy** via network inference process
- ❑ An intelligent sampling algorithm to **sample** the **most informative** traffic flows
- ❑ An **efficient** compressive sensing inference technique to **accurately estimate** highly fluctuated flows over time/space



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## iSTAMP: Formulation

Design the aggregation matrix  $A$  which provides both optimal aggregated and per-flow direct measurements

### Definitions:

- $X$ : An  $n \times 1$  vector of unknown flows denoted
- $A = \begin{bmatrix} A_g \\ A_K \end{bmatrix}$ : An  $m \times n$  binary matrix aggregation matrix
- $Y$ : An  $m \times 1$  vector of observations

$$Y = AX \Rightarrow Y = \begin{bmatrix} Y_g \\ Y_K \end{bmatrix} = \begin{bmatrix} A_g \\ A_K \end{bmatrix} X$$

### Main Optimization Framework:

$$\hat{X} = \underset{X}{\text{minimize}} \|Y_g - A_g X_g\|_2^2 + \lambda \|X_g\|_1$$

$$\text{s.t. } X_k = A_k X_k, \quad X_g \geq 0$$

### Example:

$$Y = \begin{bmatrix} Y_g \\ Y_K \end{bmatrix} = \begin{bmatrix} x_1 + x_2 \\ x_4 + x_6 \\ x_3 \\ x_5 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix}$$

TCAM	
Prefix Key	Statistics
$c_1$	$y_1$
$Y_g = A_g X$	
$c_i$	$y_i$
$c_m$	$y_m$
$Y_K = A_K X$	
$c_{m+1}$	$y_{m+1}$
$c_T$	$y_T$

$T=m+K$

### TCAM Rules

Flow ID's bit map	0	0	X	---
	0	1	X	---
	1	1	0	---
	1	1	1	---

3 most significant bits

- $x_1$ : 000.---
- $x_2$ : 001.---
- $x_3$ : 110.---
- $x_4$ : 010.---
- $x_5$ : 111.---
- $x_6$ : 011.---

## iSTAMP: Optimal Aggregation & Per-Flow Measurement Matrix Design

Measurement matrix design depends on the size of matrix and estimation technique

### Optimal Compressive Sensing Flow Aggregation

$$\hat{X} = \underset{X}{\text{minimize}} \|X\|_1 \quad \text{s.t.} \quad Y_g = A_g X \Leftrightarrow \underset{A_g}{\text{minimize}} \|A_g^T A_g - \phi\|_F^2$$

Formulated as a Linear Integer Optimization Problem

### Optimal Sampling and Exponential Aggregation Technique

#### Algorithm Modified Upper Confidence Bound (MUCB)

**Input:** Time horizon  $T_c$  and parameter  $\alpha$ .  
**Output:** At each epoch  $t$ , the set of sorted indices of incoming flows ( $I^t$ ) in descending order where  $I^t = I_k^t \cup I_g^t$ .  
**while** True **do**  
 - Set  $t = 1$ , measure all  $n$  flows  $\{x_j\}_{j=1}^n$  using all  $T$  entries of TCAM over  $\lceil \frac{n}{T} \rceil$  epochs, and set  $t_c = n$ .  
**while**  $t < T_c$  **do**  
 - Compute flow indices  $I_j^t = \alpha \bar{x}_j + \sqrt{\frac{2 \ln(t_c)}{t_j(t_c)}}$  for all flows  $j = 1, \dots, n$  where  $\bar{x}_j$  is the average flow size for  $j^{\text{th}}$  flow,  $t_j(t_c)$  is the number of times flow  $j$  has been measured up to time  $t_c$  and  $t_c$  is the overall number of measurements done so far.  
 - Sort the set  $I^t$  and report indices in descending order as  $I^t = I_k^t \cup I_g^t$ .  
 - Allocate  $k$  measurement entries to the  $k$  flows with indices in  $I_k^t$  and measure them.  
 -  $t = t + 1$ ,  $t_c = t_c + K$ .  
**end while**  
**end while**

#### Algorithm 2 Exponential Aggregation Technique (EAT)

**Input:** Aggregation parameters  $\rho$  and  $\delta$ .  
**Output:** Aggregation Matrix  $A_g^t$ .  
**Initialization:** Set  $i_c = 0$  and  $A_g^t = 0_{m \times n}$ .  
**for**  $i = m$  to 1 **do**  
 -  $r = \lceil \rho(n - K)^{\frac{1}{\delta}} \rceil + 1$   
**for**  $j = 1$  to  $r$  **do**  
 -  $A_g^t(i, I_g^t(i_c + j)) = 1$   
**end for**  
 -  $i_c = i_c + r$   
**end for**

