AAA: High Agile Adaptive Application-awareness Network for SDN

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***Abstract*—The abstract goes here.**

1. Introduction

With the data traffic and network scale rapidly increaing, there exists huge demand for scalable network management. Meanwhile, network monitoring and application awareness play a increasingly critical role in Quality of Service(Qos),Traffic Engineering(TE) and cyber security. Briefly, application awareness is a basic technology to enhance automation and intelligence of the network. It is divided into two processes: packet acquisition and traffic identification. Packet acquisition refers to capturing packets from switches through a mechanism or an algorithm. Traffic identification refers to parsing the five-tuple information of packets from different layer according to OSI model ,then recognizing the application layer protocol with the help of DPI tools. Application-aware network can improve the visibility of itself , promote integration of different business and eliminate faults quickly .However, the application awareness need integrate the high precision,high efficiency with real time, which is still a challange owing to the volume and variety of data in the large-scale network.

Software-defined network (SDN) is a new technical architecture which decouple the network control plane from the data-forwarding plane. It advocates building an open and programmable network to provide flexible, central controlled(or centralized) and globally visible network services, through which SDN can facilitate the operation and maintenance of the data center(DC) network. In a software-defined network, packet acquisition depends on OpenFlow(OF) protocol,which is varied from the Netflow and Sflow used in traditional networks.

Based on port, payload, and traffic behavior characteristics, DPI can identify a variety of information including the application layer protocol of a data flow, and be applied in application-aware network. In traditional networks, DPI devices are bound to the data plane, which makes it impossible to visualize global fine-grained traffic in real time. Therefore,many people are concerned about the research and optimization of the combination of SDN and application awareness. However, most of the current solutions are to deploy DPI in the SDN controller.In this case, parsing each single packet will be computationally heavy for controller. In addition, network scale, number of sampling nodes, sampling frequency and repetition rate of packet all increase performance consumption of controllers.On the other hand, in order to improve the accuracy of application recognition, the system must be able to capture continuous packets of the same flow regarding to the characteristics of DPI. To solve the above problems, a agile, adaptive and cooperative sampling mechanism which can be applied to large-scale data center network is urgently needed.

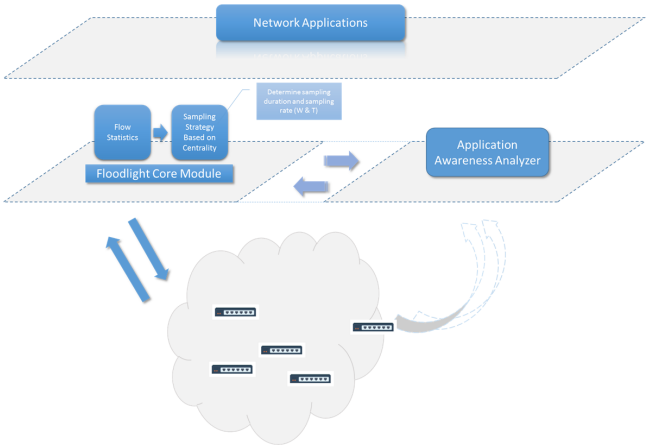


Figure 1: The System Architecture Of AAA

2. Related Work

- A detailed introduction to the background: Why build an application-aware network - the contrast between traditional and SDN networks.
- Introducting the problems existing in building a large-scale application-aware network (a reasonable collection of traffic in a large-scale network environment is a basic problem in the field of traffic monitoring and traffic engineering).
- And including the solutions already on the basic problem, and the various problems that exist.
- Introducting the Intermediary centrality algorithm.
- Outline the algorithms and strategies we use.

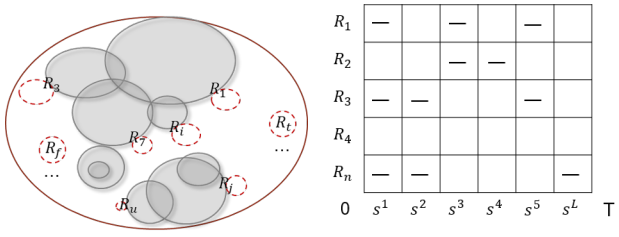
3. System Model and Design

3.1. Overview of Model

After selecting the nodes with high influence and covering all the traffic through the algorithms in 3.1 and 3.2, and determining the sampling duration and sampling rate of each switch, the controller will send the sampling instruction, and the switch will follow the set Time to sample. However, in addition to the previous two steps, the sampling strategy includes the final collaborative strategy, that is, the relationship between the traffic and the topology between the switches, and the network is coordinated with each other in a certain time or space. The flow in the stream is accurate and efficient (reducing the meaningless repeating packets). We present a variety of collaborative strategies, and finally compare their accuracy in sampling, packet repetition rate, and friendliness to the collector.

This is a simple sampling method. When the sampling point and sampling rate are determined, the controller unifies the sampling instruction and the sampling instruction to stop sampling. That is to say, in this mode, each sampling point is performed at the same pace and without additional complicated control. Shows in Figure.5.

Because R is the same, they can sample or stop at the same rhythm.



(a) area coverage (b) time slot allocation

Figure 2: overview of model

3.2. Sampling Point Selection

In large-scale DC networks, while all the switches sample flows, the excessive frequency of sending flow tables and group tables will cause extra overhead for SDN controller. Therefore, we need a strategy that can select a small number of most influential sampling nodes so that the number of flows sampled by these nodes is close to or equal to the global nodes. We may find the situationis is very similar to the graph theory. In a subnet topology, based on the concept of graph theory, we regard switches as nodes and regard flow paths as edges. Therefore, we define a flow information matrix. Then we calculate betweenness centrality and the most influential nodes has the maximal betweenness centrality. As show in Algorithm 1, the strategy is called sampling node election algorithm based on betweenness centrality.

The principle of the algorithm will be stated next, with respect to the notations in Table I being used throughout the paper.

Firstly, initialize the matrix M=[m_{ij}] and the betweenness centrality c_j. Fig.3-a shows a subnet topology, where there are 6 switch nodes and 6 flows. And we define: if f_i passes through sw_j, the m_{ij}=1, otherwise m_{ij}=0. After initialization,as Fig.3-b shows,we get a $I * J$ two-dimension matrix. Then calculate c_j and c_{max}.

$$c_{max} = \max\{c_j \mid c_j = \sum_i m_{ij}, i \in [1, I], j \in [1, J] \wedge i, j \in Z\} \tag{1}$$

Senondly, elect the node with highest betweenness centrality as the sampling node and change m_{ij} until each m_{ij} = 0. As shown in Fig.4, c_{max} = c_3. Hence,the sw_3 is the first sampling node. Owing to f_1,f_2,f_4,f_6 pass through the sw_3, make m_{ij} = 0(i=1,2,4,6,$j \in [1, J]$). Then we can get a new marrix M and calculate new c_j and c_{max} used for the next election. Repeating the above method, and electing the sampling node sw_4. Finally,we get S=sw_3,sw_4,when each m_{ij}=0.

Algorithm 1 Sampling Point Selection

Input:
The set of routers: R
The size of node will be selected: K
The current flow information matrix: M

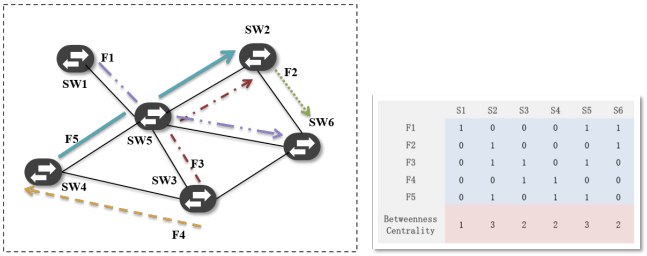
define $R^s = \{\}$ // The Set of Selected Routers
for $k = 1$; $k < K$; $k++$ **do**
  for each $R_i \in R - R^s$ **do**
    if $I_i^k > max$ **then**
      $max = I_i^k$
      $SR = R_i$
    end if
  end for
  put SR to R^s
  mark SR as R_k in R^s
end for
return R^s

TABLE 1: table

Nonation	Explanation
M	the current flow information matrix
S	selected switches set
sw_j	the j-th switch
f_i	the i-th flow
m_{ij}	the each value for f_i and sw_j in M,either 1 or 0
c_j	the betweenness centrality of sw_j
c_{max}	the max betweenness centrality of sw_j
I	the current number of flows
J	the current number of switches

3.3. Allocation of Time Slot

3.4. Order of Time Slot



	S1	S2	S3	S4	S5	S6
F1	1	0	0	0	1	1
F2	0	1	0	0	0	1
F3	0	1	1	0	1	0
F4	0	0	1	1	0	0
F5	0	1	0	1	1	0
Betweenness Centrality	1	3	2	2	3	2

Figure 3: Intermediary center based on the number of streams

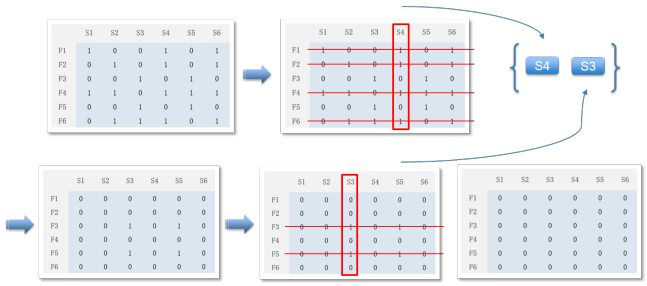


Figure 4: Sampling Point Selection

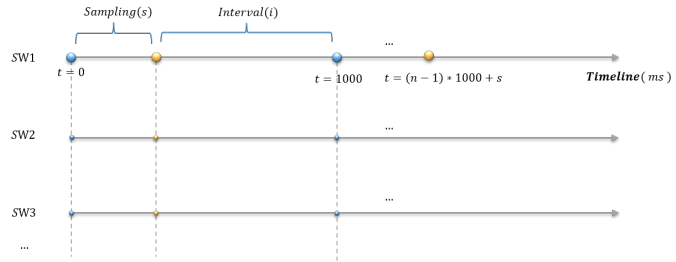


Figure 5: Simultaneous Sampling

4. Experiments and results

- Schematic diagram of strategy
- Algorithm
- Union/Find Grouping

5. Conclusion

- Lab environment
- Sampling accuracy comparison
- Sampling repetition rate comparison
- Greedy centrality algorithm experimental results
- Deduplication rate algorithm comparison

TABLE 2: 110 Switches & 22 Hosts & 1400 Flows Comparison In Real Topology

Strategy	Captured	Sampling Accuracy	Repeat Rate
Single Time Sampling	1069	0.764	36.05%
Even-Divsion Time Sampling	1094	0.7814	12.86%
One More Back-up Sw	1152	0.7979	15.78%

Algorithm 2 Sampling Point Selection Based on Centrality Measure

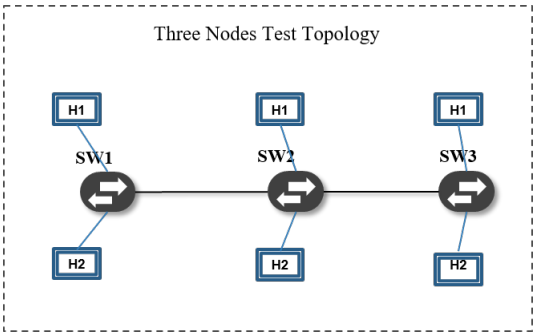
Input: M , S , c_j

while $M! = O$ **do**
  if c_{max} = c_j **then**
    Selecting sw_i
  end if
  Puting sw_j into S;
  for all f_i which $m_{ij} = 1$ **do**
    for all sw_j which $j \in [i, J]$ **do**
      if $m_{ij} = 1$ **then**
        $m_{ij} = 0$
      end if
    end for
  end for
end while
return S

Algorithm 3 Allocation of Time Slot Based on XXX

Input: M , S , c_j

return S



(a) Test Toplogy

Flow Information Matrix (M)

	S1	S2	S3
F1	1	1	1
F2	1	1	1
F3	1	1	0
F4	1	1	0
F5	0	1	1
F6	0	1	1
F7	1	0	0
F8	1	0	0
F9	0	0	1
F10	0	1	0

(b)Flow Information Matrix

Figure 6: This is total name.

- Experimental comparison of adaptive co-sampling algorithm

Algorithm 4 Order of Time Slot Based on XXXXX

Input: M , S , c_j
1: **return** S

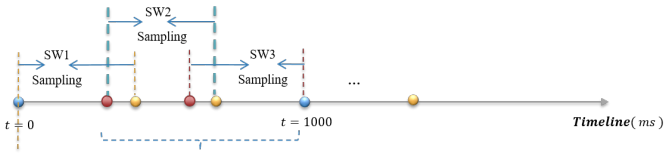


Figure 7: Even time-division sampling

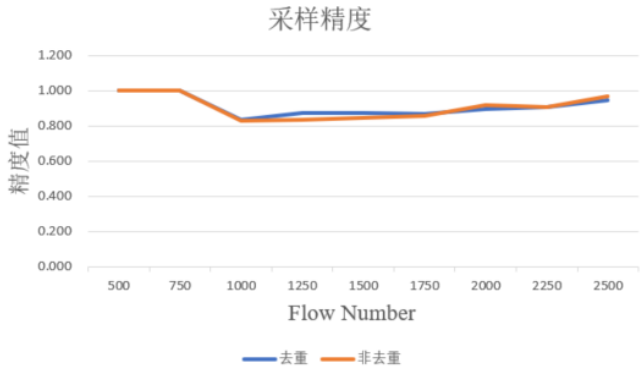


Figure 8: The definition of agile application-aware network

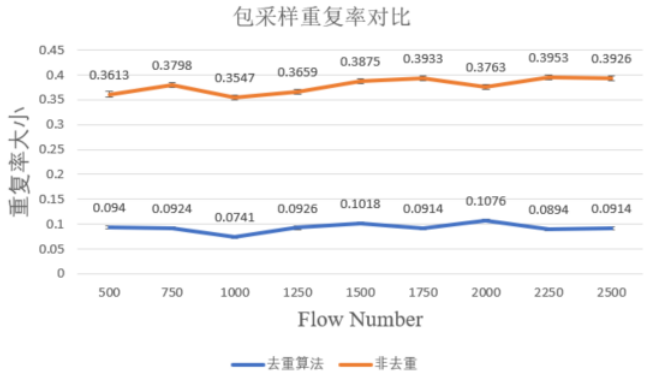


Figure 9: The definition of agile application-aware network

TABLE 3: Cost Matrix

	S1	S2	S3
S1		4	2
S2			4
S3			

TABLE 4: Comparison

Sampling Order	Cost	Accuracy	Packet Repeat Rate
(S1,S2,S3)	8	100.0%	20.46%
(S3,S1,S2)	6	100.0%	15.50%

References

[1] S. Yoon, T. Ha, S. Kim and H. Lim, Scalable Traffic Sampling using Centrality Measure on Software-Defined Networks, in *IEEE Communications Magazine*, pp.43-49, July 2017.

[2] M. Malboubi, L. Wang, C.N. Chuah, P. Sharma, Intelligent SDN based Traffic (de)Aggregation and Measurement Paradigm (iSTAMP), in *IEEE INFOCOM*, Apr 2014.

[3] L. Tong and W. Gao, Application-Aware Traffic Scheduling for Workload Offloading in Mobile Clouds, in *IEEE INFOCOM*, pp.1-9, Apr 2016.

[4] J. Jiang, S. Ma, B. Li and B. Li, Symbiosis: Network-Aware Task Scheduling in Data-Parallel Frameworks, in *IEEE INFOCOM*, pp.10-14, Apr 2016.

[5] P. Bakopoulos, K. Christodoulopoulos, G. Landi et al, NEPHELE: An End-to-End Scalable and Dynamically Reconfgurable Optical Architecture for Application-Aware SDN Cloud Data Centers, in *IEEE Communitions Magazine*, pp.178-188, Feb 2018.

[6] J. Xu, J.Y. Wang, Q. Qi, H.F. Sun and B. He, IARA: An Intelligent Application-aware VNF for Network Resource Allocation with Deep Learning, in *IEEE SECON*, pp.1-3, June 2018.

[7] J. Suh, T.T. Kwon, C. Dixon, W. Felter and J. Carter, OpenSample: A Low-latency, Sampling-based Measurement Platform for Commodity SDN, in *IEEE ICDCS*, pp.228-237, July 2014.

[8] Z. Su, T. Wang, Y. Xia and M. Hamdi, CeMon: A Cost-effective Flow Monitoring System in Software Defined Networks, in *Computer Networks*, pp.101-115, Dec 2015.

[9] N.F. Huang, C.C. Li, C.H. Li, C.C. Chen,C.H. C and I.H. Hsu, Application Identification System or SDN QoS based on Machine Learning and DNS Responses, in *APNOMS*, pp.407-410, Sept 2017.

[10] S. Jeong, D. Lee, J. Hyun, J. Li, and J.W. Hong, Application-aware Traffic Engineering in Software-Defined Network, in *APNOMS*, pp.315-318, Sept 2017.

[11] G. Cheng and Y. Tang, eOpenFlow: Software Defined Sampling via a Highly Adoptable OpenFlow Extension, in *IEEE ICC*, pp.1-6, May 2017.

[12] S. Zhao and D. Medhi, Application Performance Optimization Using Application-Aware Networking, in *IEEE NOMS*,pp.1-6, Apr 2018.

[13] M. Malboubi, S.M. Peng, P. Sharma and C.N. Chuah, A Learning-based Measurement Framework for Traffic Matrix Inference in Software Defined Networks, in *Computers & Electrical Engineering*, Dec 2017.

[14] K. Bilal, S.U. Khan, L. Zhang et al, Quantitative comparisons of the state-of-the-art data center architectures, in *Concurrency & Computation Practice & Experience*, Dec 2017.

TABLE 5: 15 Switches & 30 Hosts & Around 1000 Flows Comparison In Test Bed

Strategy	Packet Repeat Rate
Greedy Algorithm	4.39%
Random	5.93%

TABLE 6: 110 Switches & 22 Hosts & Around 1000 Flows Comparison In Real Topology

Strategy	Packet Repeat Rate
Greedy Algorithm	6.03%
The Most Bad	7.54%
Random	7.11%