Joint Data Streaming and Sampling Techniques for Detection of Super Sources and Destinations

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Definitions and Problem

- Fan-out/Fan-in: the number of distinct destinations/sources a source/destination communicates during a small time interval.
- Super Source and Destination: the sources/destinations having a large fan-out/fan-in.
- Problem: How to detect super sources and destinations in near real-time at a high speed link (e.g., 10 Gbps or 40 Gbps).

Example Motivating Applications

- Detection of port-scans: a port-scan launcher is a super source.
- Detecting DDoS attacks: the victim is a super destination.
- Internet worms: an infected host is a super source.
- "hot spots" in P2P or CDN networks: a busy server/peer is a super destination.

Previous Approaches

- Maintaining per-flow state (Snort and FlowScan): prohibitive fast memory consumption
- Triggered Bitmap scheme [Estan et al. IMC'03]: not complete
- Hash-based flow sampling [Venkataraman et al. NDSS'05]: not accurate

Our Tools to attack the problem

- Network data streaming: process each and every packet passing through to glean the most important information for answering a class of query using a small yet well-organized data structure.
- Sampling: classical technique to reduce the processing load
- Close collaboration between them

Our Schemes

- The simple scheme: filtering after sampling
- The advanced scheme: separating identity gathering and counting

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Limitation of Traditional Hash-based Flow Sampling



Limitation of Traditional Hash-based Flow Sampling

- If a flow is sampled (i.e., hash value < p), all packets belonging to it need to be processed by the hash table.
- p has to be much smaller than the ratio between the operating speed of the hash table and the arrival rate of the traffic.
- small sampling rate leads to large estimation error.

How to Overcome the Limitation?



The Design of the Data Streaming Module

• The data structure is very simple, i.e., a bit array.



• The operation is also very simple.

sampled packet

dst src









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Accuracy

- unbiased estimator
- its approximate variance is given by

$$Var[\widehat{F}_s] \approx \frac{\sum_{j=1}^{pF_s} \frac{w - u_j}{u_j}}{p^2} + \frac{F_s(1-p)}{p}$$

Our Schemes

- The simple scheme: filtering after sampling
- The advanced scheme: separating identity gathering and counting

System Model



Online streaming module

2D bit array A



Identity sampling module

- The purpose is to capture the identities of potential super sources that will be used to look up the previous 2D bit array to obtain their fan-out estimations.
- Use aforementioned filtering after sampling technique
- Use different recording strategy: only record the sampled source identities sequentially in DRAM instead of construct-ing a hash table.

Estimation module

- Given a source s, we compute $h_i(s)$, i = 1, 2, 3, to obtain 3 column vectors A_1, A_2 and A_3 (viewed as bit arrays).
- Let the set of $\langle src, dst \rangle$ pairs hashed into A_i be T_i . F_s , the fan-out of s, is approximately equal to $|T_1 \cap T_2 \cap T_3|$.
- if there are more than one sources hashed into the same 3 columns A_1, A_2, A_3 , $|T_1 \cap T_2 \cap T_3|$ actually is the sum of the fan-outs of all these sources.

Estimation module (Con't)

• Whang et al. proposed a fairly accurate estimator of $|T_i|$ based on A_i in 1990, say,

$$\widehat{T_i}| = m \ln \frac{m}{U_{T_i}} \tag{1}$$

where m is the size of A_i and U_{T_i} denotes the number of "0"s in $A_i.$

• According to the inclusion and exclusion principle, we have $\widehat{F}_s \approx |T_1 \cap T_2 \cap T_3|$ $\approx |T_1| + |T_2| + |T_3| - |T_1 \cup T_2| - |T_1 \cup T_3| - |T_2 \cup T_3| + |T_1 \cup T_2 \cup T_3|$

Accuracy

- almost unbiased
- its approximate variance is given by

$$\begin{split} &Var[\widehat{F_s}] \approx -m \sum_{i=1}^{3} f(t_{T_i}) - m \sum_{1 \leq i_1 < i_2 \leq 3} f(t_{T_{i_1} \cup T_{i_2}}) \\ &+ 2m(f(t_{T_1 \cup (T_2 \cap T_3)}) + f(t_{T_2 \cup (T_1 \cap T_3)}) + f(t_{T_3 \cup (T_2 \cap T_1)})) \\ &+ 2m \sum_{1 \leq i_1 < i_2 \leq 3} f(t_{T_{i_1} \cap T_{i_2}}) \\ &- 2m(f(t_{T_1 \cap (T_2 \cup T_3)}) + f(t_{T_2 \cap (T_1 \cup T_3)}) + f(t_{T_3 \cap (T_2 \cup T_1)})) \\ &+ mf(t_{T_1 \cup T_2 \cup T_3}) \\ & \text{where } f(t) = e^t - t - 1. \end{split}$$

Evaluation

- Traces from USC, UNC and NLANR
- simulate our schemes running on a fully utilized OC-192 (10 Gbps) using 128KB SRAM.
- For the simple scheme we set a flow sampling rate of 25% which is required to fit in 128KB SRAM.
- Both online streaming model and identity sampling module of the advanced scheme have enough speed to process the incoming traffic with 100% sampling.









Conclusion

- filtering after sampling: the simple scheme
- separating identity gathering and counting: the advanced scheme

Thank you!

- We thank to IMC and GTISC for supporting our travel.
- Questions?