CutSplit: A Decision-Tree Combining Cutting and Splitting for Scalable Packet Classification

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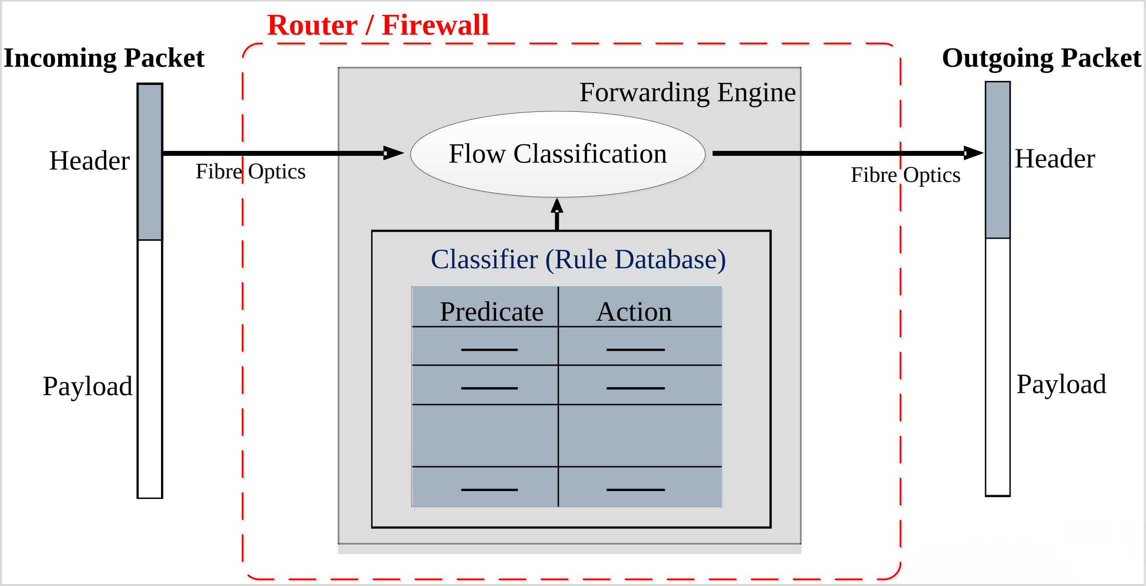
Outline

- Background
- Challenge Review
- Proposed CutSplit
- Evaluation
- Conclusion

Multi-field Packet Classification

- **Key for policy enforcement in packet forwarding**
  - Firewall, QoS, OpenFlow, P4, etc.



#	An example OpenFlow 1.0 classifier/flow table (12-tuple)						Action
r_1	**Ingress Port**	**Ether src**	**Ether dst**	**Ether type**	**VLAN id**	**VLAN priority**	$Action_1$
	3	*	*	*2048*	*	*	
	IP src	**IP dst**	**IP proto**	**IP ToS bits**	**TCP/UDP Src Port**	**TCP/UDP Dst Port**	
	15.25.70.8/30	*18.15.125.3/28*	*0x11/0xff*	*1*	*1024 : 65535*	*80*	

…

Previous Works & Key Metrics

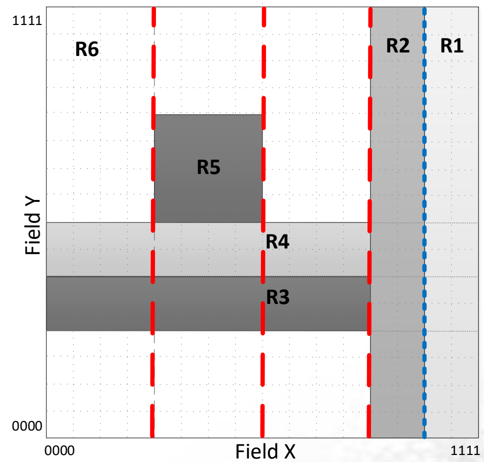
- **Taxonomy of previous packet classifications**
  - **Algorithmic**: Desired but speed/memory inefficient
  - **Architectural**: Fast but expensive, power hungry, poor scalability and suffer from range expansion
- **Key metrics of scalable packet classification**
  - Low memory consumption
  - Low memory accesses
  - Bounded worst-case performance
  - Low pre-processing time
  - Low incremental update time
- **Our proposed algorithm: CutSplit**
  - A decision-tree based algorithmic approach

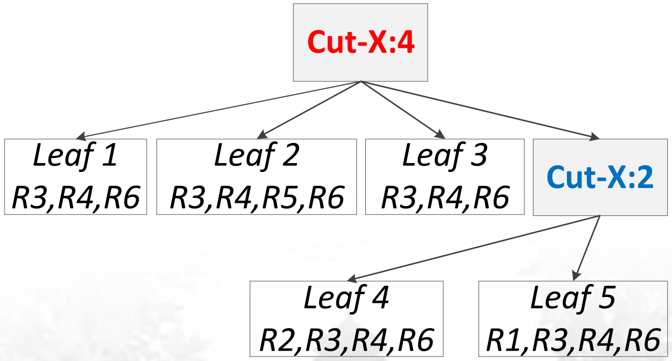
A Little Review on Decision-trees

Decision-tree construction in packet classification

- 1. Rule table matching ↔ Point location in geometric space
- 2. Partition the searching space into sub-spaces recursively
  - Root node: Whole searching space containing all rules
  - Internal node: #rule covered by sub-space > a predefined number of rules
  - Leaf node: #rule covered by sub-space <= a predefined number of rules

Rule #	Field X	Field Y	*Action*
R1	111*	*	*A1*
R2	110*	*	*A2*
R3	*	010*	*A3*
R4	*	011*	*A4*
R5	01**	10**	*A5*
R6	*	*	*A6*





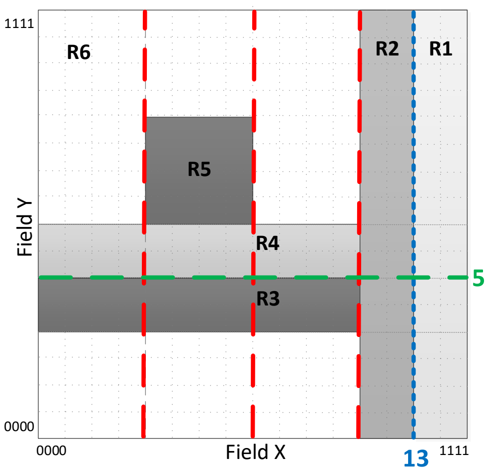
HiCuts-4

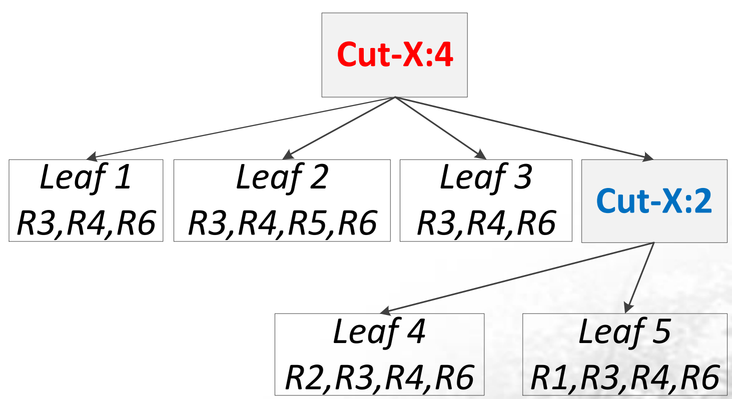
Two major threads of building decision-trees

- **Equal-sized cutting & Equal-dense splitting**

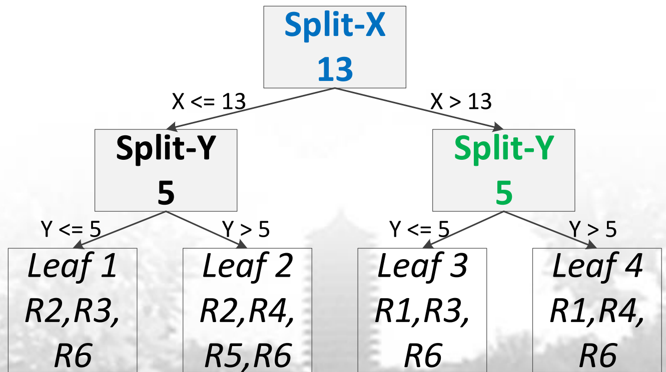
Two Major Threads in Decision-trees

- **Equal-sized cutting based decision-trees**
  - Separate the searching space into many equal-sized sub-spaces
  - e.g., HiCuts, HyperCuts, EffiCuts, HybridCuts, etc.
- **Equal-dense splitting based decision-trees**
  - Unequal-sized sub-spaces containing nearly equal number of rules
  - e.g., HyperSplit, ParaSplit, SmartSplit, etc.





HiCuts-4



HyperSplit-4

Why Yet Another Decision-tree?

A well established problem

without

Well established solutions

Scalability	HyperSplit	EffiCuts	HybridCuts	SmartSplit
Memory consumption	X	√	√	√
Memory accesses	X	X	√	√
Worst-case performance	√	X	X	X
Pre-processing time	X	X	X	X
Incremental update	X	X	X	X

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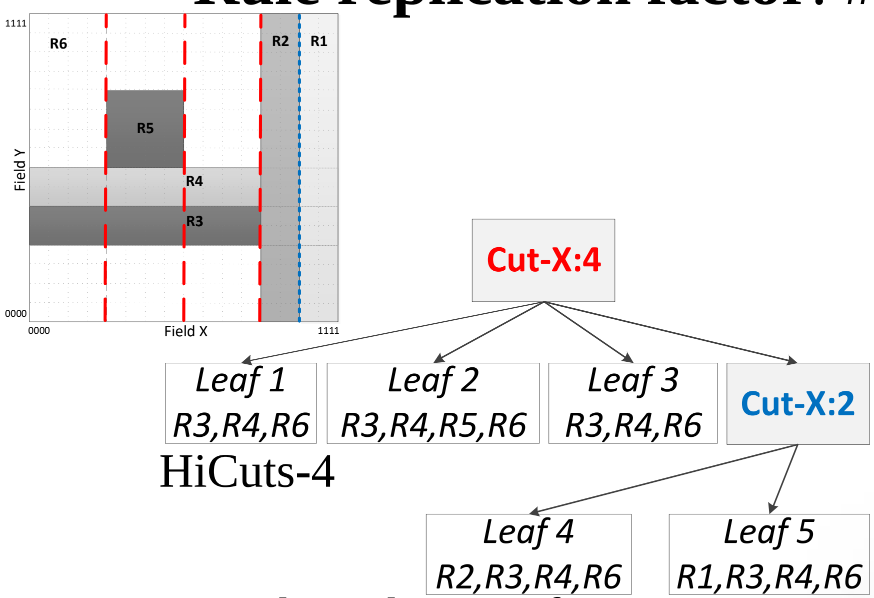
Review & Analysis on Challenges

Rule replication: Main trouble-maker for decision-trees

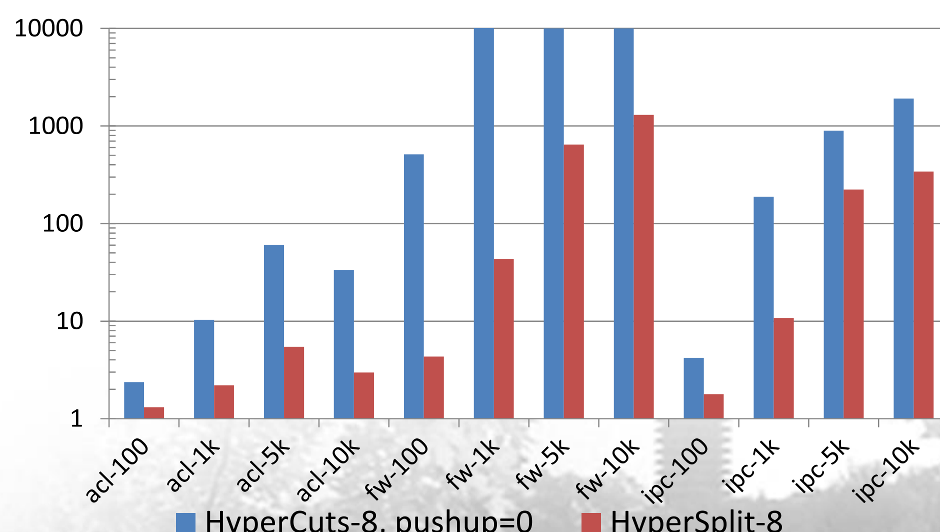
- In case a rule spans multiple sub-spaces/nodes in decision-tree, **rule replication** happens, which is an undesirable case.

More insights on rule replication

- **Rule replication factor**: #stored rules / rule set size



Rule replication factor:
(3+4+3+4+4)/6=3

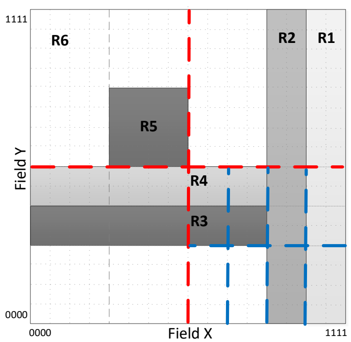


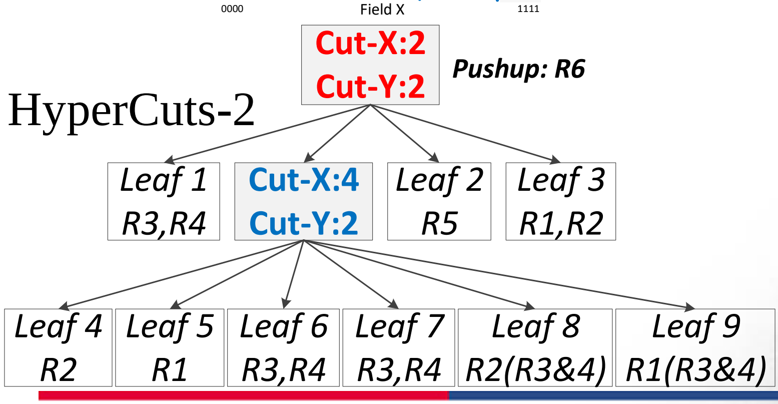
Evaluation of *rule replication factor* for different rule sets

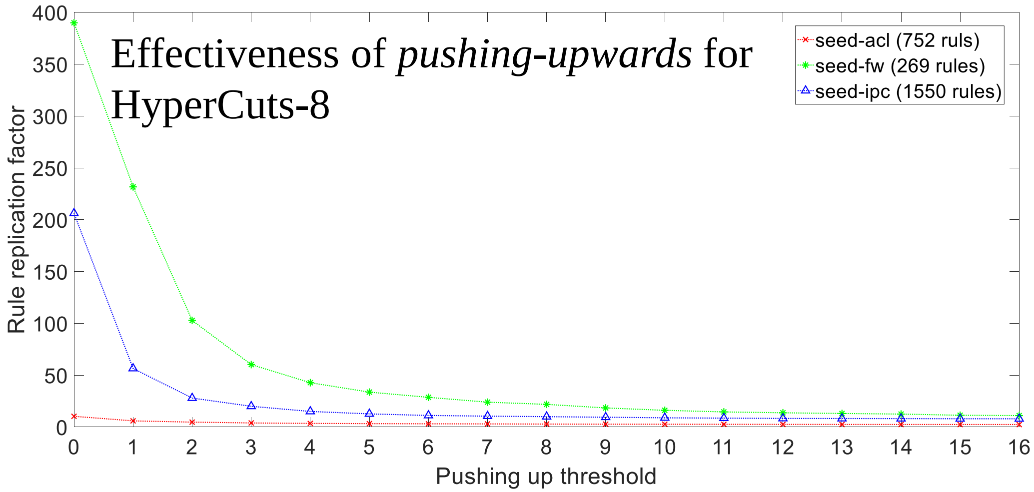
Review & Analysis on Prior Art

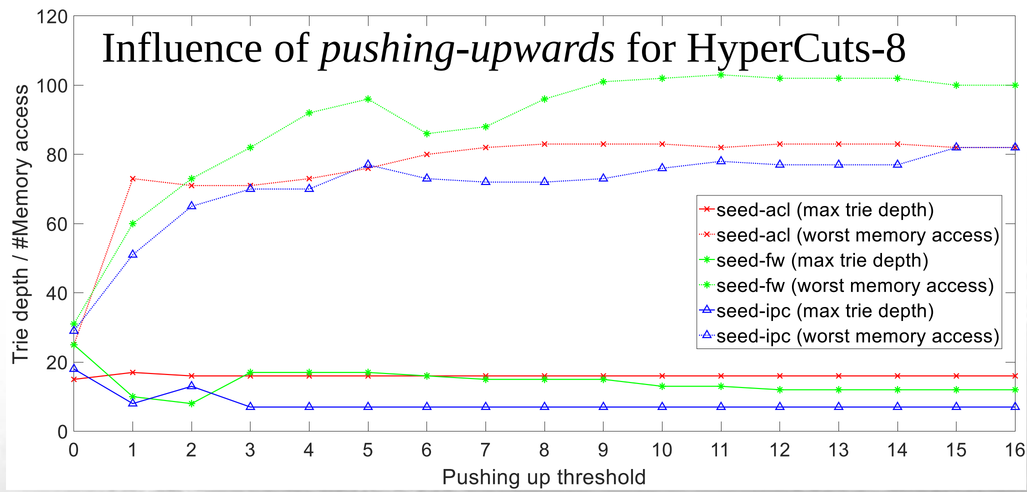
☐ Recent efforts: Effectiveness & Influence

- **Optimization methods**
  - ***pushing-upwards***
  - *rule overlap*
  - *region compaction, etc.*





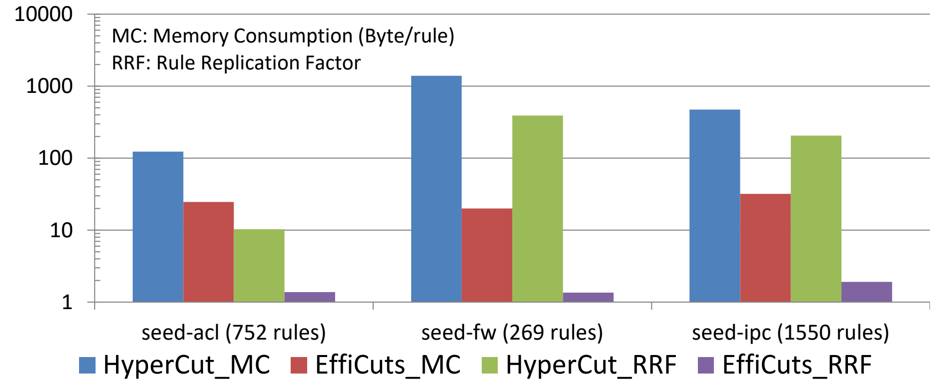




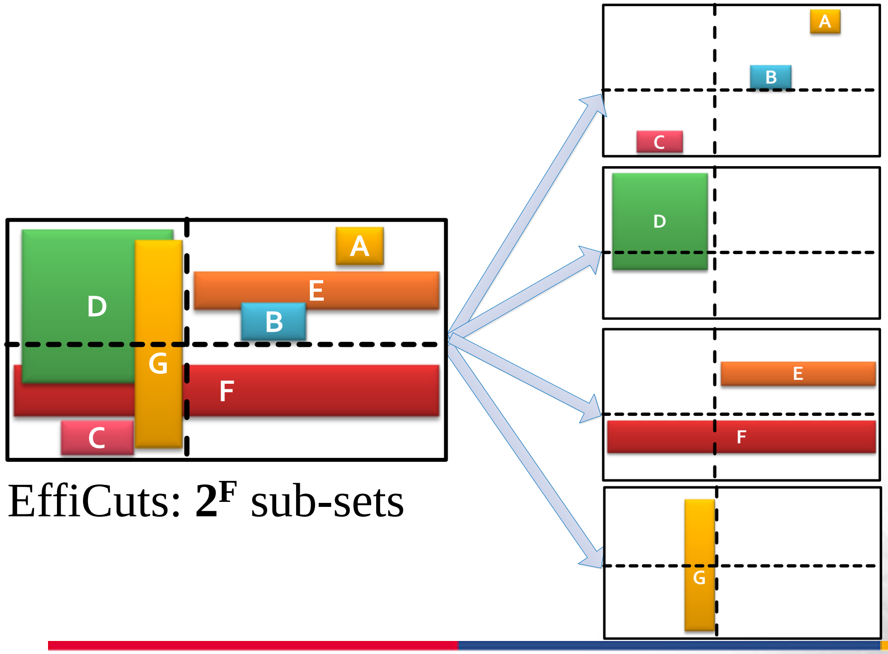
Review & Analysis on Prior Art

Recent efforts: Effectiveness & Influence

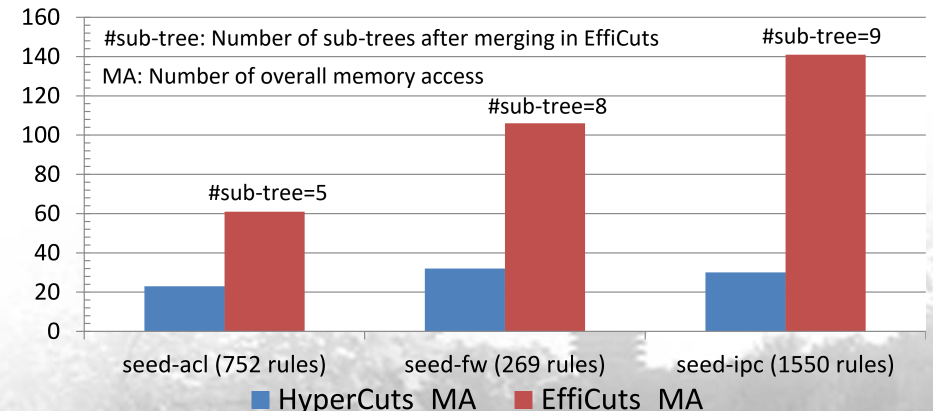
- Optimization methods
- **Rule set partitioning**
  - **all field based: EffiCuts**
  - single field based: HybridCuts
  - IP address based: SmartSplit



Effectiveness of *rule set partitioning* for EffiCuts-8



EffiCuts: $\mathbf{2^F}$ sub-sets



Influence of *rule set partitioning* for EffiCuts-8

Review & Analysis on Prior Art

Recent efforts: Effectiveness & Influence

- Optimization methods
- Rule set partitioning
- **Cutting or Splitting?**
  - EffiCuts: **HyperCuts** + Equi-dense cutting option (i.e., splitting)
  - HybridCuts: One- + multi-dimensional cuttings (i.e., **HyperCuts**)
  - SmartSplit: {**HyperCuts**, HyperSplit} based on *memory estimator*
  - **However**, the performance of these algorithms drop quickly with the size of rule sets increases: Poor scalability of HyperCuts & HyperSplit

Thus, these efforts reduce *rule replications* while sacrificing search or update performance!

Better Solutions?

No optimization method
(with better search & update performance)

+

More scalable rule set partitioning
(with less rule groups)

+

Better combination of Cutting & Splitting
(by exploiting characteristics)

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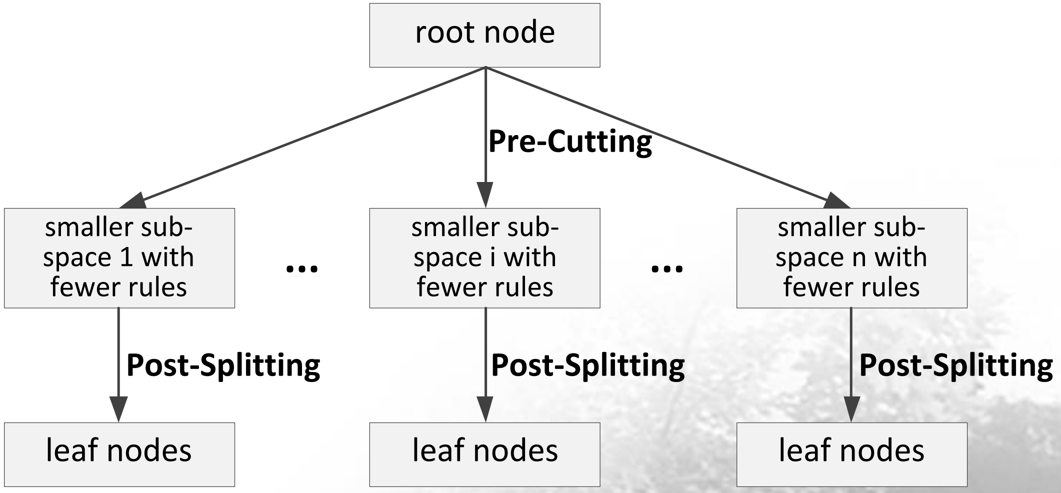
Ideas & Framework

- **Cutting** can separate searching space into **smaller** sub-spaces quickly for faster classification
- **Splitting** can significantly reduce *rule replications* and offer a bounded worst-case search performance for **small** rule sets

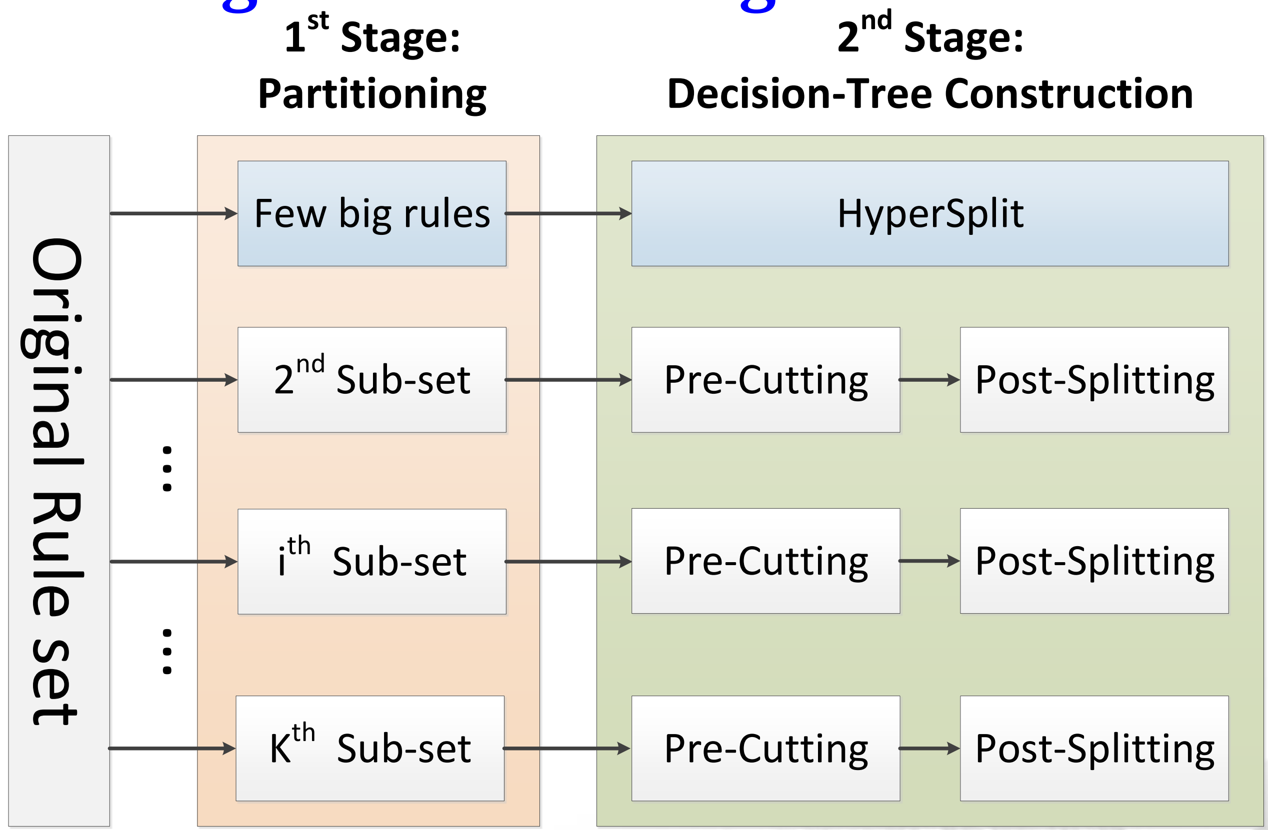
To foster the strengths and circumvent the weaknesses of cutting and splitting, the idea directly perceived is to combine the following two strategies: Faster Pre-Cutting & Explicit Post-Splitting



The framework of CutSplit

More details & Challenges

☐ Preprocessing & Constructing search structure

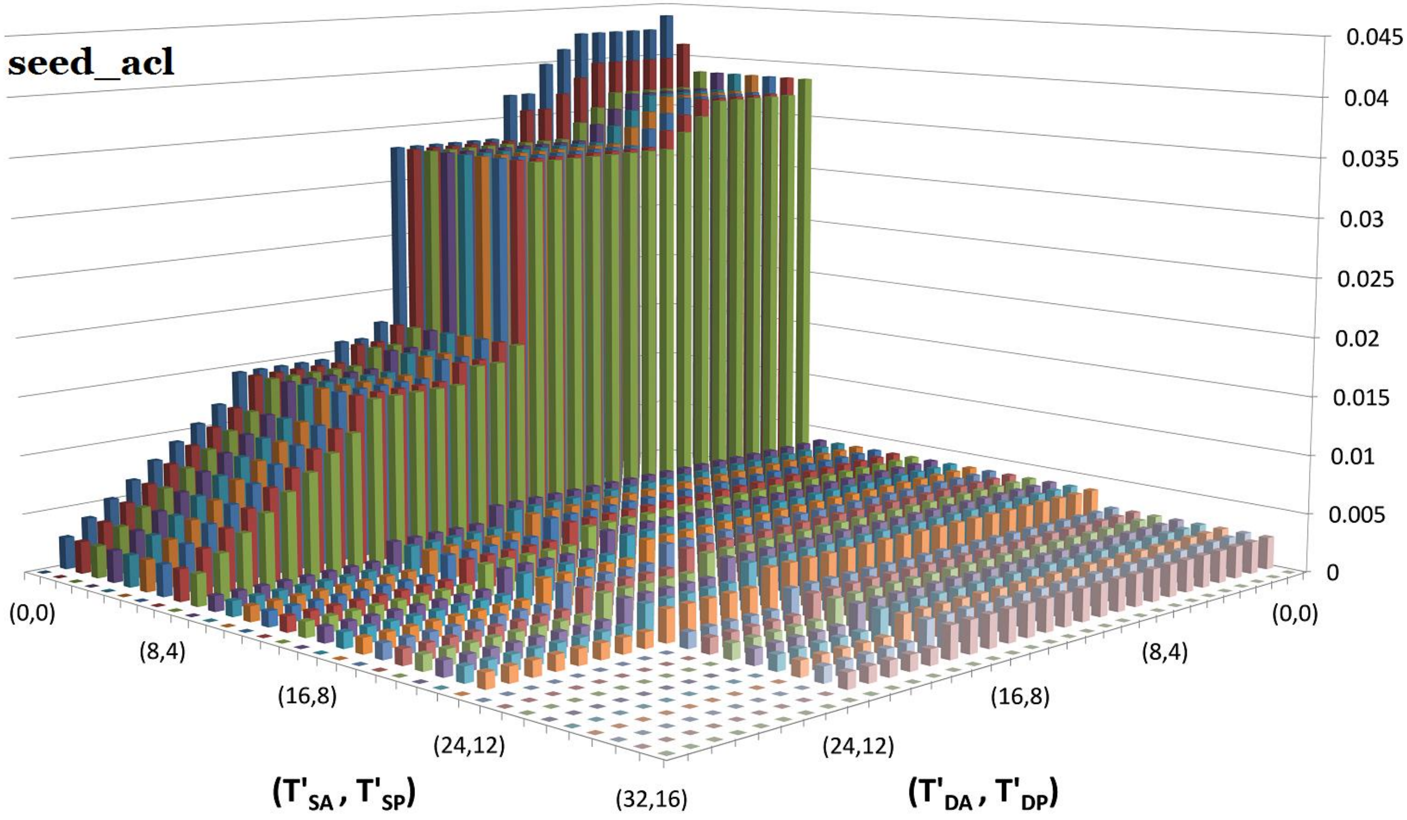


Fewer sub-sets
(Not only for 5-tuple)

No/Fewer rule replication
No optimization in cuttings

Observations (1)

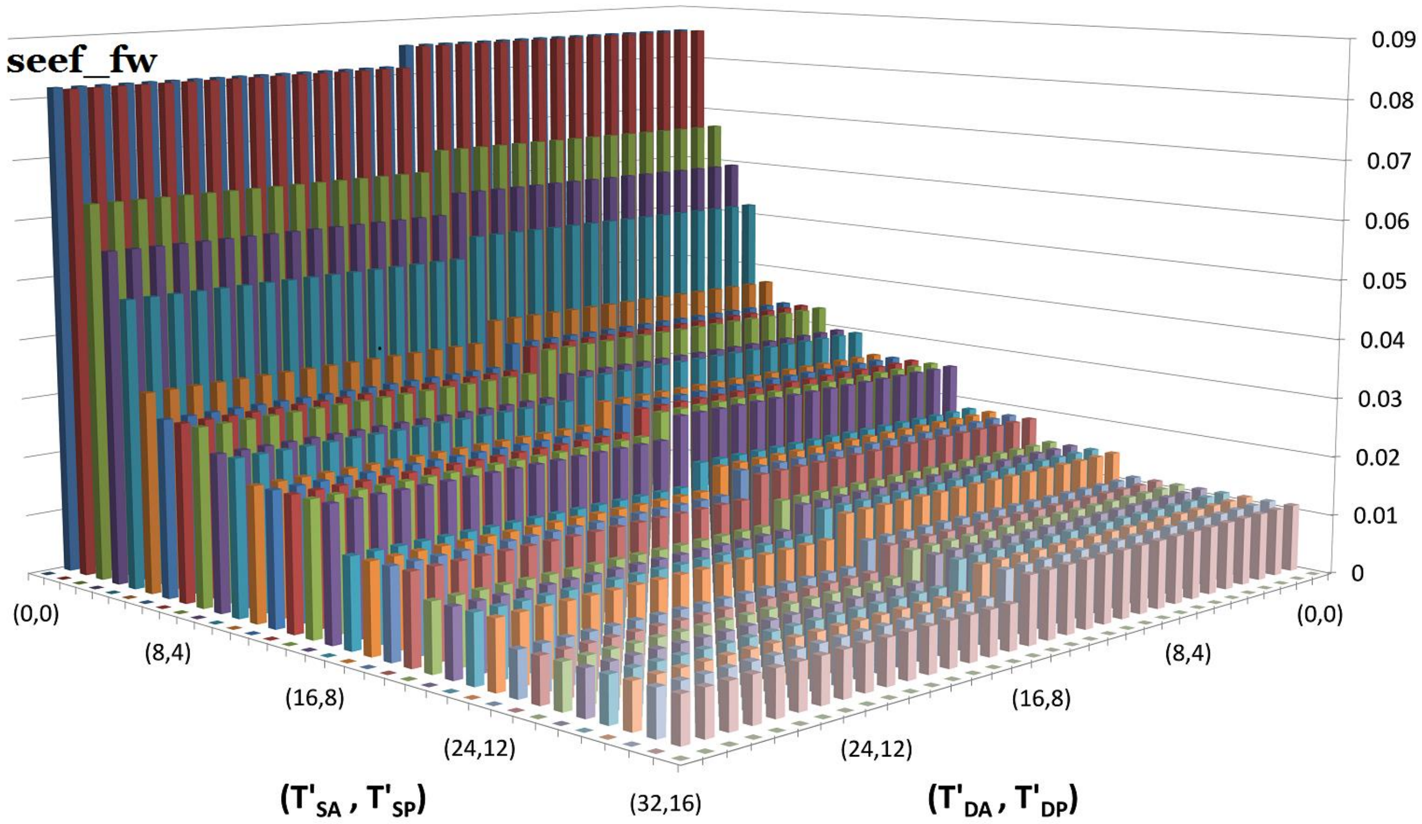
- ☐ **At Least One *Small Field***



The ratio of *big rules* for *seed-acl* rule set

Observations (1)

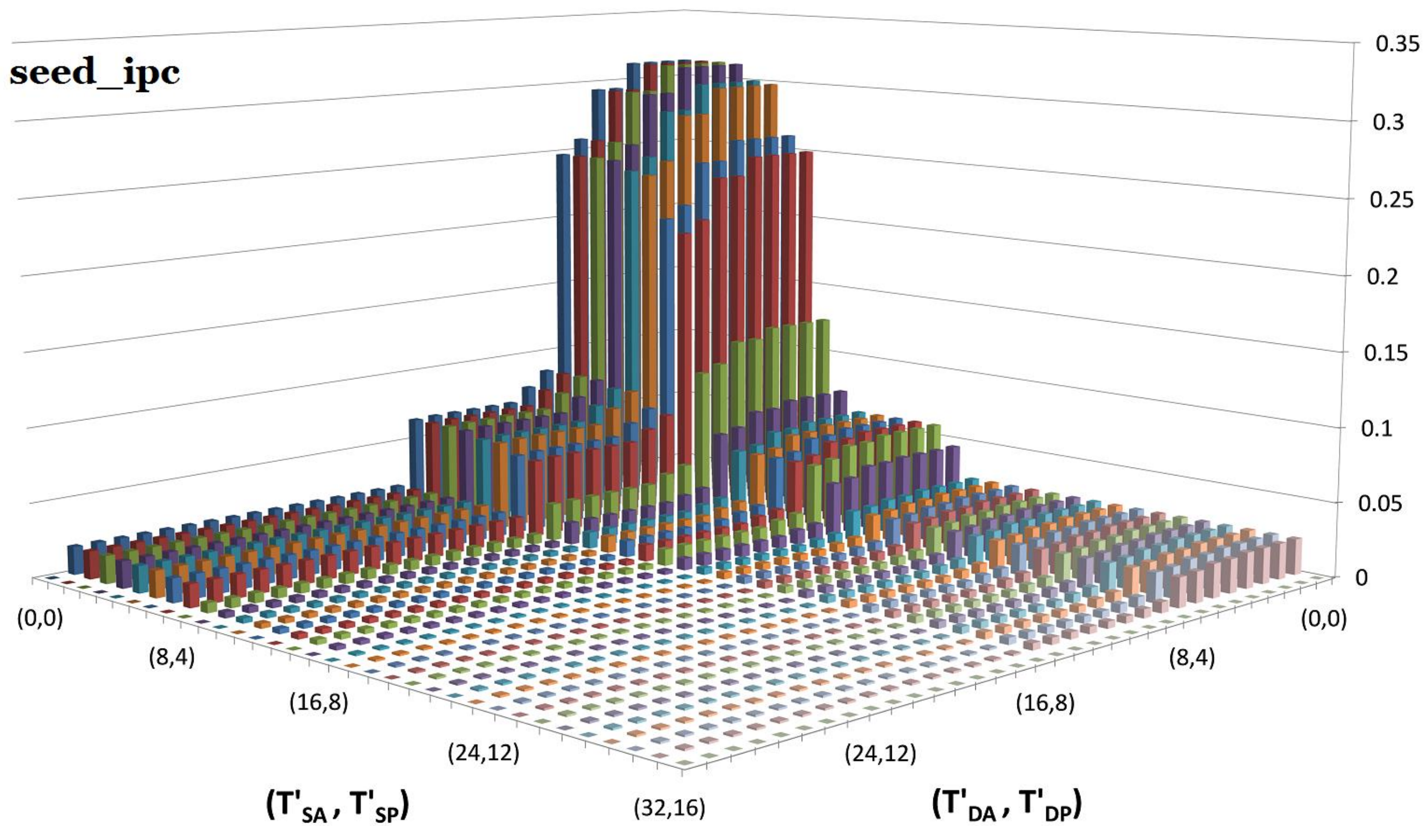
- At Least One *Small Field*



The ratio of *big rules* for *seed-fw* rule set

Observations (1)

- At Least One *Small Field*



The ratio of *big rules* for *seed-ipc* rule set

Observations (2)

☐ Very Few *Small Fields*

Table. Statistical results for 5-tuple & OpenFlow-like rules (Assuming the value of T_i is half of range length in field F_i)

Rule set(#rules)	Number of *big rules*	Number of *small-k* rules				
		k=1	*k=2*	*k=3*	*k=4*	*k⩾5*
seed-acl(752)	3	749	739	425	0	0
seed-fw(269)	4	265	218	17	2	0
seed-ipc(1550)	2	1548	1472	789	5	0
* openflow-1(716)	0	716	708	655	426	0
* openflow-2(864)	0	864	852	761	429	0

Mahalo

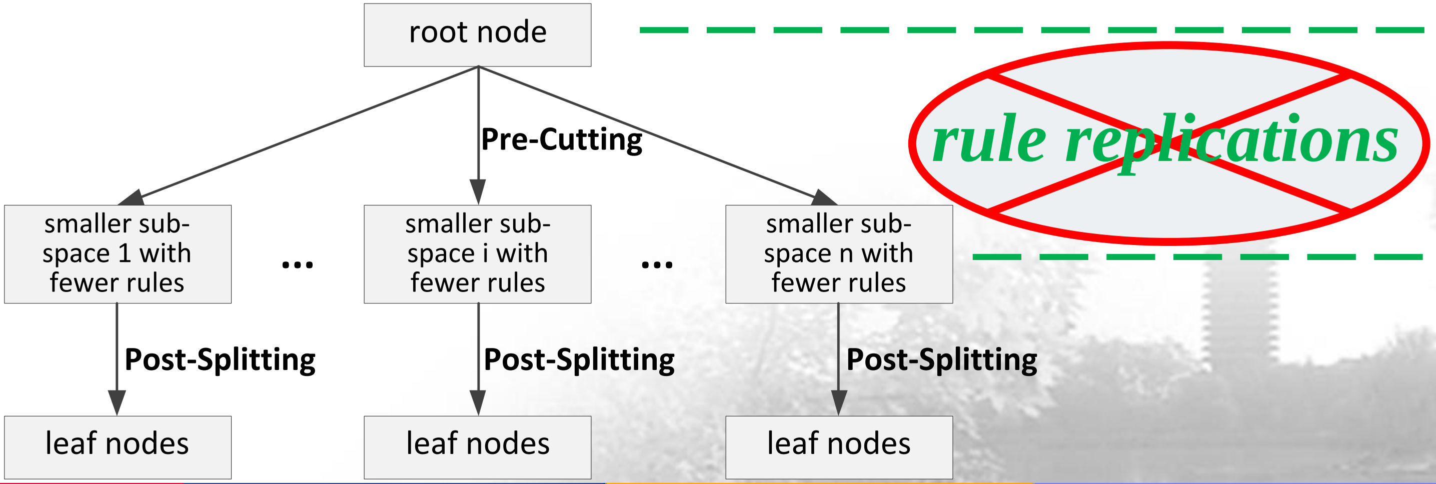
***The two OpenFlow-like rule tables are generated by Tsinghua University, which are based on 216 real-life rules from enterprise customers. We are very grateful to Pro. Jun Li for his selflessness help in this evaluation.**

Scalable Partitioning

- **Step 1:** Remove very few *big rules*
  - HyperSplit for these rules
- **Step 2:** Select a few distinct fields
  - Top-k significant *small fields* (e.g., >95% rules included)
  - Remove remaining rules to *big rules* in Step 1
- **Step 3:** Fields-wise partitioning
  - *M* fields selected for *F*-tuple rule sets → 2^M-1 sub-sets
- **Step 4:** Selective subset merging
  - Sub-set with very few rules → Sub-set with fewer *small fields*

Decision-Tree Constructions

- **CutSplit: Pre-Cutting + Post-Splitting**
  - **Pre-Cutting** on *small fields*
    - Simpler & More efficiently → **No** optimization (e.g., FiCuts)
  - **Post-Splitting** on small sub-sets after cuttings
- **When to switch to Post-Splitting?**
  - Achieving threshold value → **No** rule replication in cutting stage



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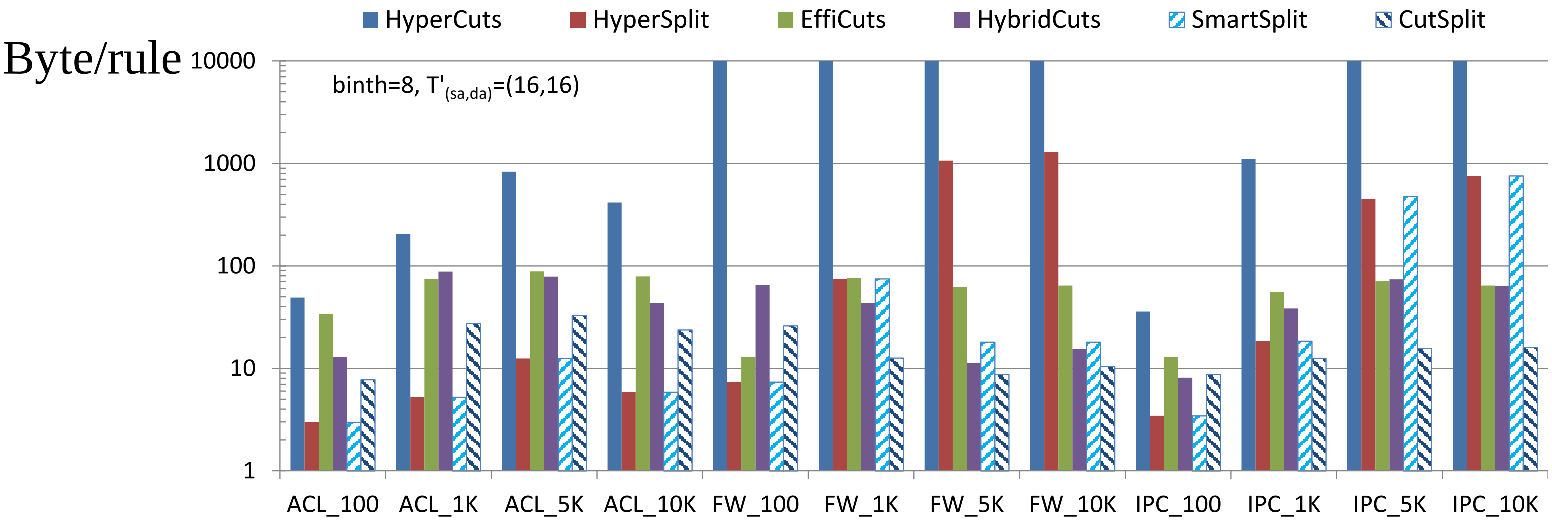
Experimental Setup

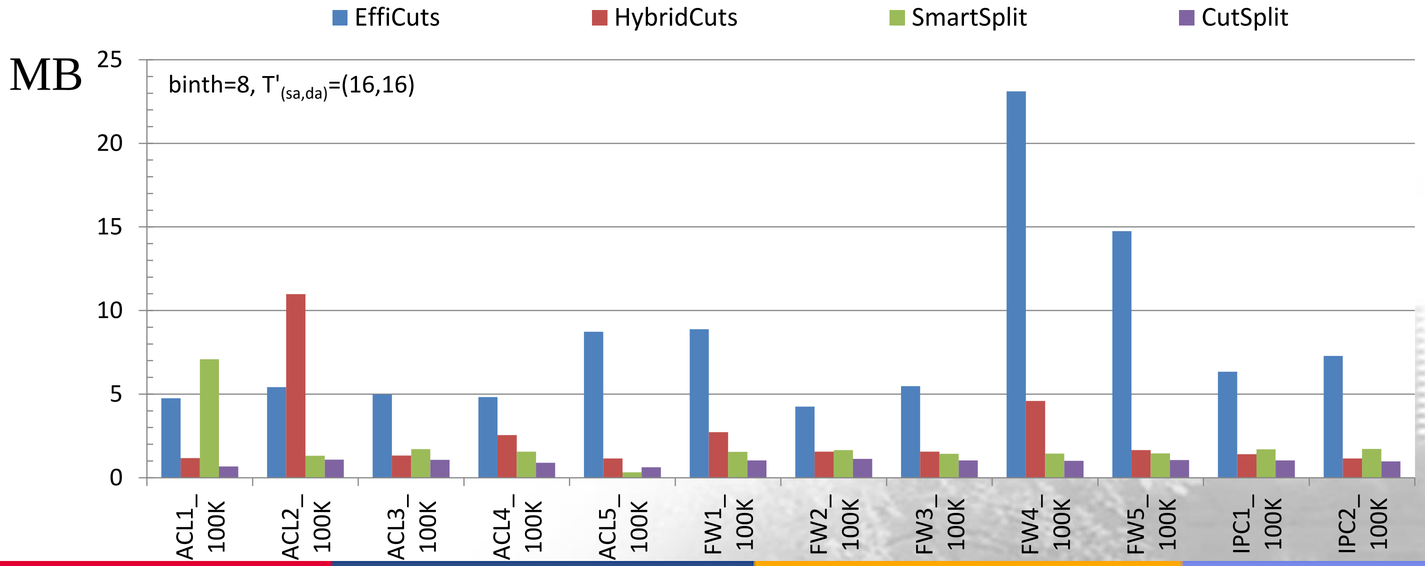
- **Tested with**
  - Publicly available rule sets from Washington University
    - Used the ACL & FW & IPC 100, 1K, 5K, 10K
  - ClassBench
    - Generate ACL & FW & IPC 100K
- **Compared with**
  - Cutting based: HyperCuts, EffiCuts and HybridCuts
  - Splitting based: HyperSplit and SmartSplit
- **Primary metrics**
  - Memory consumption (Decision-tree data structure)
  - Memory accesses
  - Pre-processing time: decision-tree & sub-trees

Mahalo

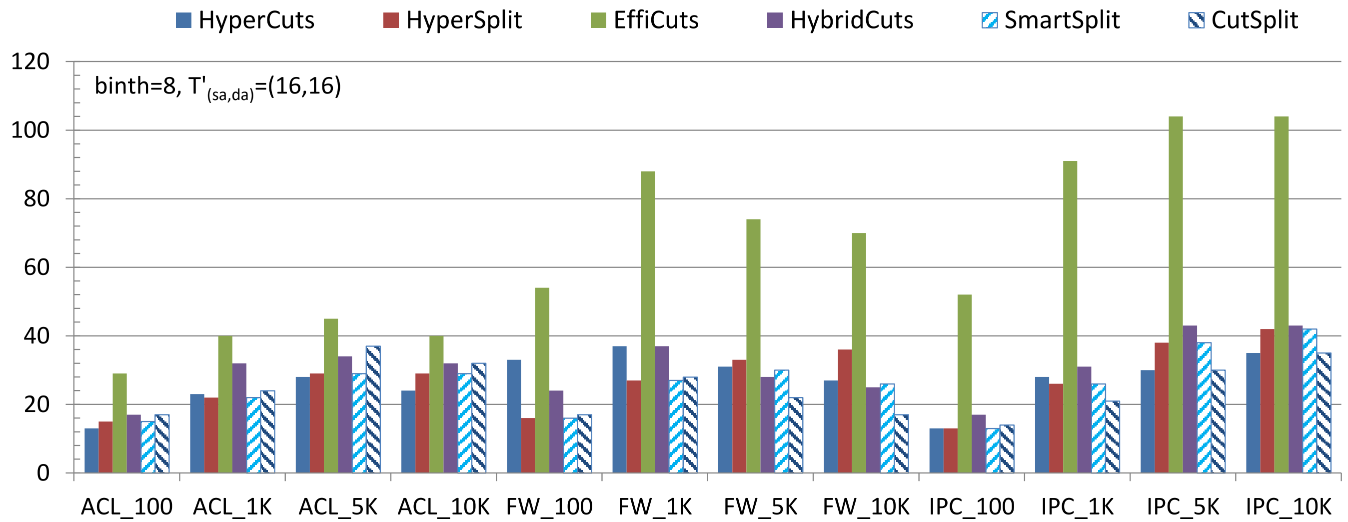
Many thanks to authors of HyperCuts & HyperSplit & EffiCuts for their selflessness help (source codes) in evaluations. As a response, our implementation of CutSplit is publicly available in http://wenjunli.com/CutSplit/

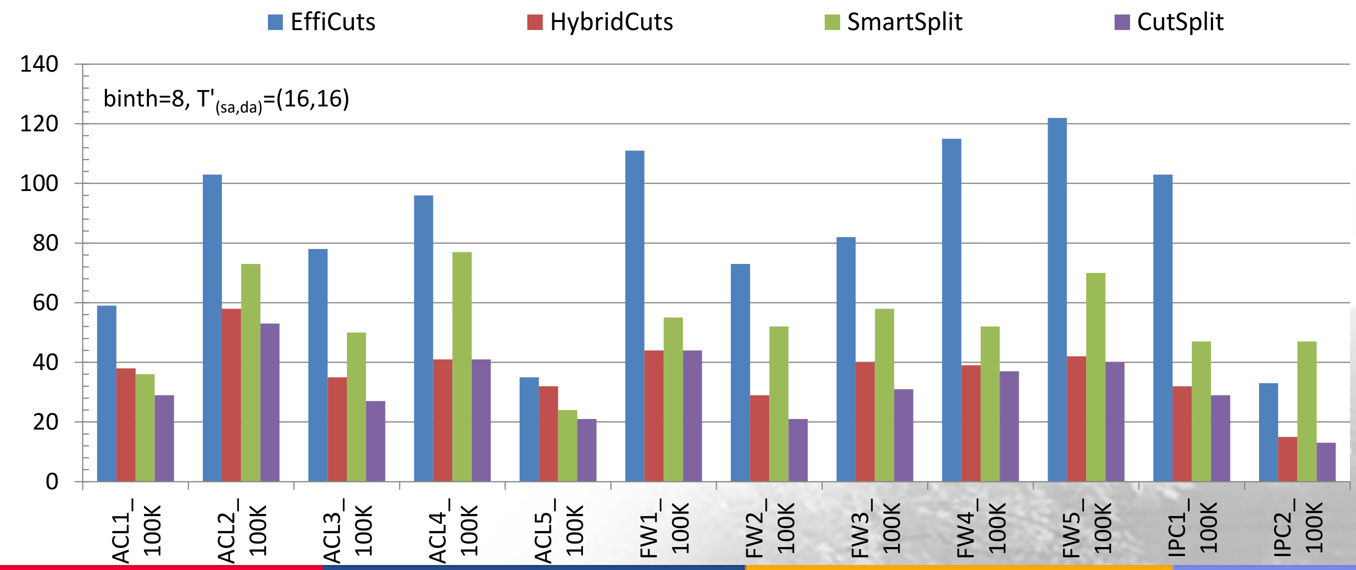
Memory Consumption





Memory Accesses





Pre-processing time: Decision-Tree

Table IV. Pre-processing time for decision-tree construction (s)

Rule set	EffiCuts	HybridCuts	SmartSplit	CutSplit
ACL1_100K	4784.4	183.1	632.5	11.7
ACL2_100K	8338.4	91.0	427.4	4.1
ACL3_100K	8453.6	148.6	6403.7	2.6
ACL4_100K	8232.6	161.8	3336.1	3.4
ACL5_100K	8905.3	138.5	2695.9	3.0
FW1_100K	4250.7	165.1	1392.1	3.0
FW2_100K	2842.2	161.9	1652.9	2.5
FW3_100K	4281.2	187.8	3855.4	3.0
FW4_100K	1662.1	280.3	4553.6	3.5
FW5_100K	3778.4	179.2	3212.7	2.7
IPC1_100K	8615.0	151.5	3133.4	2.6
IPC2_100K	6070.4	229.6	3187.9	2.6
MEAN	5851	173	2874	3.7

Pre-processing time: Sub-trees

Table V. More details about splitting based sub-trees in CutSplit

Rule set	Number of rules		Pre-processing time (us)	
	Worst-case	*Average*	*Worst-case*	*Average*
ACL1_100K	344	17.1	569	45.6
ACL2_100K	473	25.3	6975	125.1
ACL3_100K	31	10.4	207	21.3
ACL4_100K	320	18.7	8693	168.7
ACL5_100K	93	12.8	683	28.9
FW1_100K	193	16.4	2664	71.8
FW2_100K	10	9.4	28	14.8
FW3_100K	118	14.2	1068	43.2
FW4_100K	10	9.0	23	12.9
FW5_100K	111	14.4	869	38.5
IPC1_100K	14	9.7	57	18.1
IPC2_100K	10	9.6	129	15.1
MEAN	144	14	1830	50

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Conclusion

CutSplit:

- In-depth challenge review
- Novel observations
- Scalable partitioning
- Pre-Cutting & Post-Splitting

Future Works

- Determinacy on performance
- Software-hardware combined, e.g., FPGA
- Combine with TSS, TCAM, etc.

Thank you！

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