修士論文　2001年度 (平成13年度)

# 2D Packet Classification for Internet Protocol

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## 2D Packet Classification for Internet Protocol

インターネットの発達により、ルータ内におけるパケット処理が複雑化してきた。ルータは、本来の機能であるパケット転送機能の他に、ファイアウォールやQoSといった様々な機能を持つようになった。パケットのクラス分けは、これらの機能において重要な役割を果たしている。ルータが効率良くクラス分けを行うためには、良いクラス分け手法が必要である。

本論文では、ヘッダ中の始点アドレスと終点アドレスを利用した、インターネットにおけるパケットの2次元クラス分け手法を提案する。本手法では、あらかじめ、複数の検索面を生成し、その上にフィルタを配置する。目的のフィルタを検索する際は、まず、目的のフィルタが含まれている検索面を探し出す。そして、その検索面内で、目的のフィルタを探し出す。

本手法の計算量を解析した結果、最適なフィルタを $O(\log W)$ 回の検索で発見できることが判明した。また、データ構造の構築は、$O(NW)$ 回の手順で行える。メモリ消費量は最大時に $O(N^2W)$ となるが、本手法は最大時になる確率が減少するよう設計した。本手法の評価には、模擬フィルタデータベースを用いた。その結果、メモリ消費量は $O(NW)$ であり、最大時を大きく下回った。

キーワード

1. Internet Protocol　2. packet classification　3. filter database　4. firewall
5. Quality of Service

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Abstract of Master's Thesis

Academic Year 2001

# 2D Packet Classification for Internet Protocol

The Internet's development has pushed to the more complex processing of Internet packets in routers. Routers now not only have to forward packets – their main function, but also have to perform other functions such as firewall and Quality of Service functions. The core of these functions is packet classification. Since an Internet router may perform several classifications for a packet, thus it requires a good packet classification scheme. Packet classification is to classify packets into a *flow*. Packets are said to match a flow if they meet some criterions defined by a rule, thus processed in a similar manner.

This thesis presents a scheme for classifying Internet packets based on two header fields of packets, thus called two-dimensional (2D) packet classification. The relevant header fields for this thesis are source and destination addresses. Our scheme solves packet classification problem by creating search planes based on filters in a filter database and store the filters in search planes. Our scheme finds the best matching filter for a packet using a two-step process: find the search plane containing the best matching filter, then find the best matching filter in that search plane.

Complexity analysis of our scheme shows that it can search for the best matching filter in $O(\log W)$ time. To build its data structure for a filter database, this scheme requires only $O(NW)$ time. Even though the worst-case memory requirement is $O(N^2W)$, it is designed to reduce the probability of reaching that worst-case. We evaluate our 2D packet classification scheme by running it using simulated filter databases and the simulation result shows that the memory usage tends to be $O(NW)$, rather than close to the worst-case.

Key Word

1. Internet Protocol 2. packet classification 3. filter database 4. firewall
5. Quality of Service

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# Contents

# List of Figures

# List of Tables

# List of Algorithms

# Chapter 1

# Introduction

## 1.1 Background

The Internet is a collection of interconnected hosts. These hosts are interconnected using links. Some hosts can only act as the termination point of data (end-hosts), while the others can serve as the intermediaries for end-hosts (routers). Hosts on the Internet communicate using Internet Protocol (IP) where data are exchanged in the form of IP datagram. IP datagrams packets travel from the source host to their destination through routers, and routers are responsible to forward these datagrams to reach their final destination.

The capability to forward packets is a requirement of every IP router [2]. An IP router may also do additional processing on incoming packets. The most common process added to an IP router was packet filtering for security purposes. Now, however, some IP routers perform many new additional processing to the packets, such as delivery guarantees in terms of bandwidth, delay, and jitter, and statistics for billing purposes. All these processes require IP router to classify packets into a *flow*. Packets are said to match a flow if they meet some criterions defined by a rule, thus processed in a similar manner.

The Internet's development has pushed to the more complex packet-processing in IP routers. The complexity is measured by line speed, the number of packet processing, and the difficulty level of each packet processing that must be supported by an IP router. Generally, the complexity of packet processing in a router corresponds to router's location in the Internet. If a router is located on the backbone of the Internet, packet processing in that router tends to be more complex than another router located on the leaf of Internet.

Figure. 1.1 shows the typical processing of packets inside the router. An incoming packet is first processed by *firewall* module to know whether the router can accept the packet or has to drop it. If the router accepts the packet, *QoS (Quality of Service)* module processes the packet to know whether the corresponding flow of the packet still conforms to its QoS specification. Assuming the packet is not dropped, it is then processed by *packet forwarding* module to forward the packet to the correct gateway to destination.

Now that the router knows the next-hop gateway – and the outgoing interface – of the packet, once again *firewall* and *QoS* modules process the packet. Firewall module decides whether the packet can be forwarded through the outgoing interface. If it can be forwarded, QoS module performs prioritization, packet shaping, etc., so packets' flow conforms to its specification. This is an illustration of how packets get processed by many modules in an

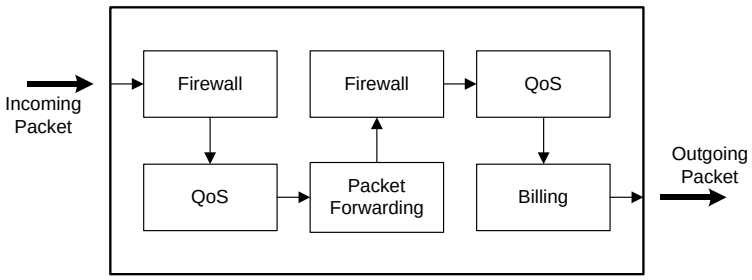



Figure 1.1: Typical packet-processing flow in an IP router.

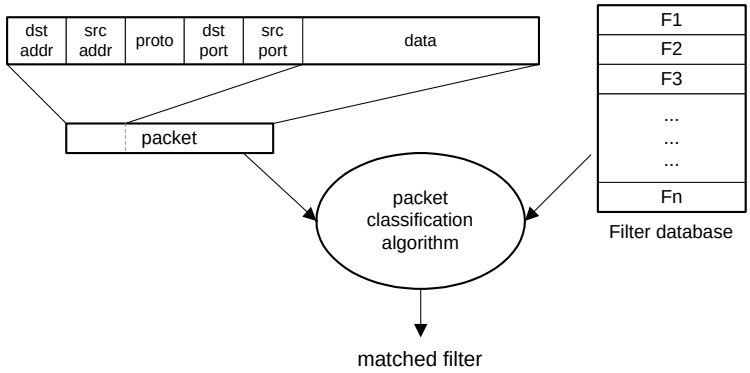



Figure 1.2: Conceptual model of packet classification.

IP router.

## 1.2 Packet Classification

The above mentioned packet processings have something in common, they have a set of rules and they match incoming packets to the rules to find which rule(s) match(es) the packet. This common function is usually called *packet classification*. Figure 1.2 illustrates the conceptual model of a packet classification.

Packet classification function has three components: a packet, a filter database, and an algorithm to classify packets. A Packet is the IP datagram to be matched with filters in the filter database. The packet has several properties that are relevant to classification: source and destination addresses, type-of-service, length, etc.

Filter database is a collection of filters (also called *rules*), and each filter consists of several fields and an action. Each field of a filter is associated to a certain property of IP packet, usually to a packet header field. Each field can be in the form of single value (e.g. 23), range (e.g. 0–1023), prefix (e.g. 203.178.143/24), or wildcard (matches all values).

A packet property matches to its corresponding filter field if the value of that property

is contained within the value range of the filter field. A packet matches to a filter if all properties of the packet match to the corresponding fields of the filter. When this happens, packet is classified into the flow defined by the filter, and will be treated according to the action of the filter.

As an example, filter database in Fig. 1.3 has three filters. This filter database defines three flows. Assuming we have a TCP packet whose source address is 202.249.47.142, destination address: 203.178.143.121, source port: 40123, and destination port: 22. This packet matches to the upper filter, thus it is *permit*-ted to enter the router. However, if the packet is an ICMP packet whose source and destination addresses are 202.249.47.142 and 203.178.148.24, then it matches to the middle filter. Therefore, it is *deny*-ed from entering the router.

```
tcp src 202.249.47/24 port * dst 203.178.142/23 port 20–23 permit
ip src 202.249/17 dst 203.178.148/25 deny
ip src * dst * permit
```

Figure 1.3: A filter database.

Packet classification algorithm performs the matching between IP packet and the filters to find which filter matches the packet. A naïve algorithm would be to compare the packet with each filter in filter database, from top to bottom, until the algorithm finds a matched filter. However, this algorithms' speed depends linearly to the number of filters in database. From the illustration of Figure 1.1, it is clear that a router may invoke packet classification function – thus, the algorithm – several times, each from different modules. Therefore, packet classification algorithm should be fast enough to allow the algorithm being executed several times and still can forward packets at line speed.

The complexity of packet classification problem depends on the number of filter fields and the number of filters that must be supported. If the number of filter fields (usually called *dimensionality*) becomes larger, then the problem becomes more complex. This also applies to the number of filters in filter database.

Packet classification can be categorized as *layer 3* or *layer 4* classification, depending on the fields of filters. Filters of layer 3 classification uses IP address fields or other packet header fields that are relevant for processing at the Internet Layer of TCP/IP protocol stack. If classification includes other fields that are only relevant to UDP and TCP, then it is called layer 4 classification.

Packet forwarding is an example of layer 3 classification. Filters for packet forwarding, the routing/forwarding table, have only one field that corresponds to destination address of an IP packet. The action of these filters is the next hop gateway for the matching packet. Fig. 1.4 shows a portion of BGP (Border Gateway Protocol) routing table of a router in Telstra Network, which contains the routing table of the whole Internet. Data from Telstra Network Australia [1] at December 5, 2001 16:03 (GMT+10) showed that the current BGP routing table holds about 100 thousand active entries (Figure 1.5) and updated at the rate of 550 times per hour on average (Figure 1.6). These data show that while packet forwarding only has one dimension, it is required to support large database and fast update.

Firewall and QoS functions – in general – are layer 4 classification since they tend to use port fields for their filter databases. Firewalls are used not only to prevent or allow traffic

| Network | Next Hop |
|---|---|
| 3.0.0.0 | 202.84.219.194 |
| 4.18.12.0/22 | 203.50.126.70 |
| ⋮ | ⋮ |
| 167.202.192.0/19 | 202.84.219.194 |
| 167.203.0.0 | 202.84.219.193 |
| ⋮ | ⋮ |
| 203.2.135.0 | 203.14.6.7 |
| 203.2.142.0 | 203.14.0.4 |

Figure 1.4: Routing table of a router in Telstra Network.

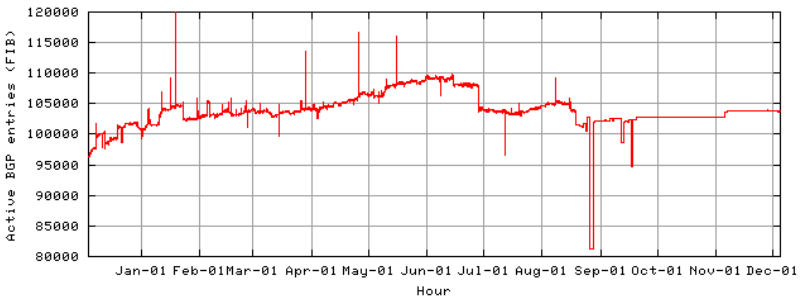



Figure 1.5: Active BGP entries in Telstra Network.

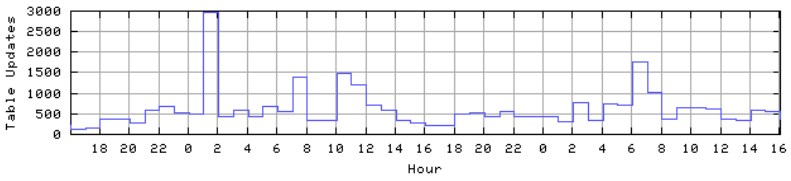



Figure 1.6: BGP update in Telstra Network.

from and to certain hosts, but also from and to certain hosts using certain applications, indicated from the protocol type and port fields. QoS function may the same port fields as firewall with the purpose of prioritization, traffic shaping, etc.

As of now, it is not clear how many filters defined in the largest firewall database on the Internet, since network administrators do not want to expose their filters due to security reasons. Firewall database obtained by others in packet classification field are less than 2000 filters [3][6][7]. No papers stated that they are using filter databases for QoS function. Despite the difficulties of obtaining real-life filter databases, it is safe to assume that filter databases for firewall and QoS are like that of BGP routing table for the IP address fields, while the port fields depend on the popular applications on the Internet.

BGP routing table is an indicator to estimate the complexity for IP address based packet classification. Each entry in BGP routing table has information about its originating AS (Autonomous System). An Autonomous System is defined as a group of IP networks operated by one or more network operators that has a single and clearly defined external routing policy and expressed as AS Number. However, owing to dropping price of telecommunication lines, many enterprises start to have connectivity to several network operators (multi-homing network) and they apply for their own AS number [5]. This fact practically means that an AS is likely to also have a policy for its firewall and QoS functions because an enterprise tend to have a policy for such functions. Therefore if BGP routing table becomes larger, then we would likely to find larger filter database.

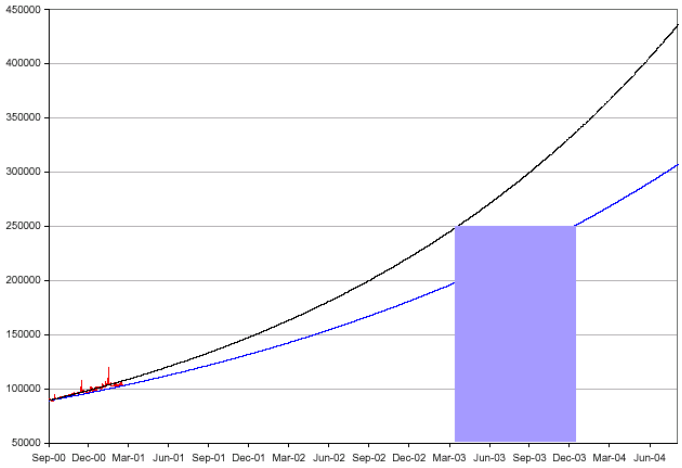



Figure 1.7: BGP table growth - projections.

In the future, BGP routing table will expand further due to increasing number of multi-homing networks [5]. Figure 1.7 shows the projection of BGP routing growth [5]. The upper and lower the projection based on the past six months and two years trends, respectively. This growth means that more IP prefixes are being advertised to the Internet. This would likely be followed by the increase of filter database size for firewall and QoS functions, mainly because their filter databases have to reflect the increase of IP prefixes on their IP address fields: source and destination addresses. Due to this projection, it is important to have two-dimensional packet classification that is capable of handling many source and

destination address filters.

## 1.3 Research Objective

The previous sections showed that IP routers might execute packet classification several times to process an IP packet. Because of this, then it is important to have good packet classification function on IP routers. Given the importance of packet classification and the outlook of BGP routing expansion, the objective of this research is to find a good scheme for classifying two-dimensional –source and destination– filters.

## 1.4 Organization of Thesis

This thesis consists of six chapters. The next chapter states the problem formally and describes related work on this field. Chapter 3 explains a two dimensional packet classification scheme, which is the idea of this thesis. Chapter 4 presents implementation and simulation result. In Chapter 5 we analyze and evaluate our scheme based on the design and simulation results, and we give summary and conclusion in the final chapter.

# Chapter 2

# Problem Statement and Related Work

## 2.1 Problem Statement

Packet classification is looking at $K$ fields in the headers of each packet that are relevant to classification. Suppose we have a packet $P$ and a filter $F$. A filter $F$ is a $K$ tuple ($F$[1], $F$[2], ..., $F[K]$) where each $F$[i], $1 \leq i \leq K$, is a filter for the corresponding field in a packet, which can be a single value, a variable length prefix bit string, or a range. Variable length prefix bit string is mostly used for address fields while range is usually used for port fields. Each filter $F$ has an action that is associated with that filter. For example, a filter might be used to block or accept a packet, or even divert it as we see in some filter applications such as *ipfw* of FreeBSD.

Each field in filter $F$ is compared to the corresponding field of packet $P$. Let $P[i]$ is the corresponding field of $F[i]$. A field $F[i]$ matches $P[i]$ if the value of $P[i]$ is within the range of $F[i]$. A filter $F$ is said to match a packet $P$ if all fields of F matches the corresponding field of $P$, i.e. $F[i]$ matches $P[i]$, $1 \leq i \leq K$. As an example, let (167.205/16, 202.249.47/24) be a filter of source and destination IP addresses. This filter matches an IP packet with source 167.205.22.108 and destination 202.249.47.142, but not an IP packet whose source and destination are 202.249.47.133 and 203.178.143.1.

A filter database consists of $N$ rules $F1$, $F2$, ..., $F$N where each filter has $K$ distinct fields. In a filter database, there is a possibility that two or more filters match a given packet so we have to have a tie breaking mechanism to define the best matching filter. To simplify the problem, let each filter in a filter database has an associated cost, if there is more than one rule match a given packet then we define the best matching filter as the least-cost filter. In practice, a filter database is usually indexed linearly and we can use the index number as the cost of the filter. A filter denoted as $F$n has $n$ as its' index number. As an example, if in a filter database, $F2$ and $F6$ match a packet $P$, then we say that $F2$ is the best matching filter for packet $P$.

This research is on the two-dimensional case of packet classification ($K = 2$). Packet headers that are relevant for this research are source address and destination address. Since IP addresses are often expressed in the form of prefix, this research assumes that every filter in the filter database can only have that form.

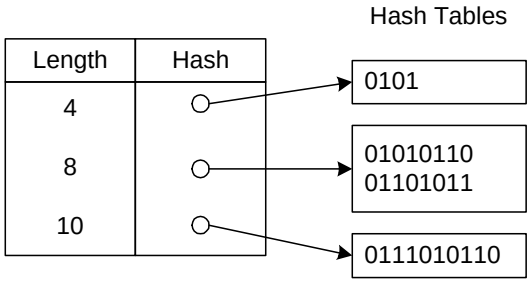



Figure 2.1: Hash tables for prefix lengths.

## 2.2 Related Work

There are many publications that are related to packet classification problem. This section summarizes four works by others. This section is closed with a table showing the comparison of several packet classification schemes.

### 2.2.1 Scalable High Speed IP Routing Lookup

Waldvogel et.al. [8] describes a new algorithm for best matching prefix using binary search on hash tables organized by prefix lengths. This algorithm requires a worst-case of $\log_2(addressbits)$ hash lookups, thus it scales very well.

There are three significant ideas of this algorithm: using hashing to check whether an address $D$ matches any prefix of a particular length; binary search to reduce the number of searches from linear to logarithmic; and precomputation to prevent backtracking in case of failures in the binary search of range.

Hashing idea is to look for all prefixes of a certain length $L$ using hashing and use multiple hashes to find the best matching prefix, starting with the largest value of $L$ and working backward.

As an example, consider a routing table of four prefix entries, each with prefix length of 4, 8, 8, and 10. Each of the entries would be stored in a hash table that corresponds to its' prefix length (Figure 2.1). The hash tables are stored as a sorted array, so for this example, the array has three entries.

Searching for address $D$, we walk through each hash table in that array starting from the largest value $l$, i.e. 10 on the example, extracting the first $l$ bits of $D$ to get its prefix of $D$. We then search the hash table using that prefix as the key. If we found a prefix, then we have found the best matching prefix (BMP) and the search terminates; otherwise if we found nothing, we move to the next entry of the array. As we see here, the worst-case search time of this algorithm is $O(W_{dist})$ hash lookups, $W_{dist}$ is the distinct prefix lengths in the database, which is less than $W$ (bit width of the address).

A better strategy for this search is to use binary search on that array. To do this, we need to put *markers* in the tables corresponding to shorter lengths to point to prefixes of greater lengths. These *markers* direct binary search to look for matching prefixes of greater length. This way, the number of hashes is cut down to $O(\log_2 W_{dist})$. Searching for an IPv4

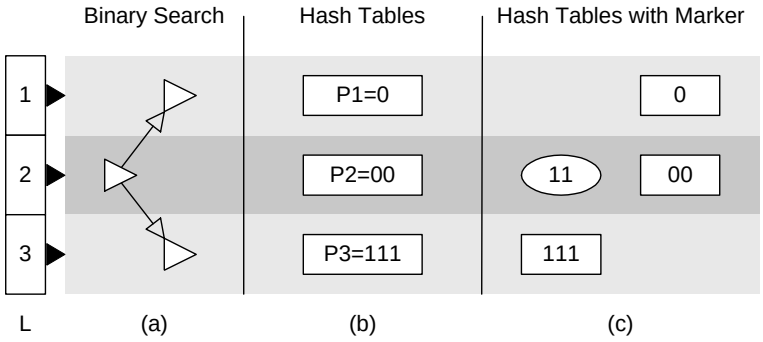



Figure 2.2: Binary search on hash tables.

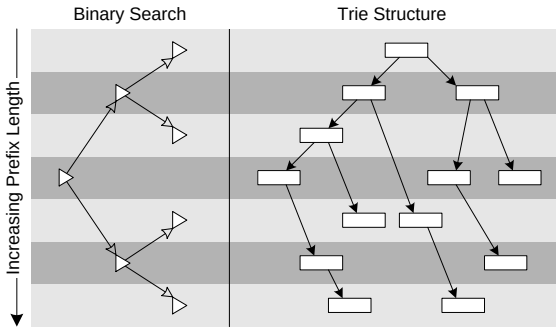



Figure 2.3: Binary search on trie levels.

address would require 5 hash accesses in the worst case.

To illustrate the binary search strategy, suppose we have three prefixes $P1 = 0$, $P2 = 00$, $P3 = 111$. Storing the prefixes in hash tables and sorting the array, we have Figure 2.2 (b). If we search for 111, binary search (a) would start at the middle of the hash table and search for 11 in the hash table containing $P2$. This search would fail and have no pointer that it should search in the longer prefix tables to find the BMP. To correct the search, we need to put the marker for prefix $P3$ in this table, thus the lookup for 11 would succeed and binary search would know that it should search for a match in the longer prefix table.

The hash tables containing prefixes and markers can be thought as a trie where each hash table is a level of a trie that corresponds to nodes of a certain prefix length (Figure 2.3. Binary search in this trie starts on the median level of the trie and depending on the result of hash lookup on that level, the search will continue to the level of shorter or longer prefix length.

Another effect of using binary search on trie levels is the number of markers is reduced to at most $\log_2 W$ markers per real prefix. This reduction is achieved because it suffices to place markers at all levels in *L that could be visited by binary search when looking for an entry whose BMP is P.*

A naïve implementation of this algorithm will take *linear* time. Markers, while can point to the BMP, they can also cause the search to follow false lead, which may fail. When this happens, we would have to modify the binary search to backtrack and search the upper half of the level of failure, and that would lead to linear time.

To avoid the backtracking problem, we need use precomputation when inserting markers. Suppose we insert a marker $M$ to the hash table, $M$ would have to record the best matching prefix of the marker ($M.bmp$). With this variable, now the binary search remembers the value of $M.bmp$ whenever a lookup produces a match. If the search in the lower half produces a failure, search procedure doesn't need to backtrack, since it remembers the best matching prefix from $M.bmp$.

Waldvogel et.al. also shows some refinements to the scheme explained above to reduce the average number of hash computations. These are *asymmetric binary search* and *mutating binary search*. Both optimizations exploit the structure of the data set. Interested readers can read [8] for the details.

### 2.2.2 Hierarchical Intelligent Cuttings

Gupta and McKeown [3] uses heuristics to solve $k$-dimensional packet classification problem. Their approach focuses on the practical implementation of classification with real-life filter database. The approach, called HiCuts (hierarchical intelligent cuttings), attempts to partition the search space in each dimension, guided by simple heuristics that exploit the structure of filter database.

The HiCuts algorithm builds a decision-tree data structure by carefully preprocessing the filter database. Each time a packet arrives, the classification algorithm traverses the decision tree to find a leaf node, which stores a small number of rules. A linear search of these rules produces the matching filter.

During the preprocessing, HiCuts creates internal nodes of the decision tree. For each internal nodes $v$, HiCuts associates some properties

- A box $B(v)$, which is a $k$-tuple of ranges or intervals.
- A cut $C(v)$, the dimension $d$ where $B(v)$ is cut, and $np(C)$, the number of equal intervals $B(v)$ is cut into in dimension $d$. This cut forms the children of $v$.
- A set of filters $R(v)$, which is a subset of filters in the filter database that collides with $v$.

HiCuts starts with a root node $v$ and store all filters $R(v)$ in that node. It then cuts the node in dimension $d$ into $np(C)$ equal intervals using heuristics that selects both parameters. Node $v$ now has $np(C)$ children nodes and HiCuts stores subsets of $R(v)$ in each children nodes. The algorithm partitions every nodes of the tree until the number of filters that collides with the node doesn't exceed a threshold, which is called *binth*. Nodes having no more than *binth* rules form the leaf nodes of the decision tree.

Figure 2.4 illustrates the geometrical representation of a two-dimensional filter database. Figure 2.5 shows a possible tree for the database. Each ellipse denotes an internal node $v$ with a triplet ($B(V)$, $dim(C(v))$, $np(C(v))$). Each rectangle is a leaf node that contains the rules. This example uses 2 as its *binth*.

The preprocessing algorithm of HiCuts uses four heuristics to partition nodes:

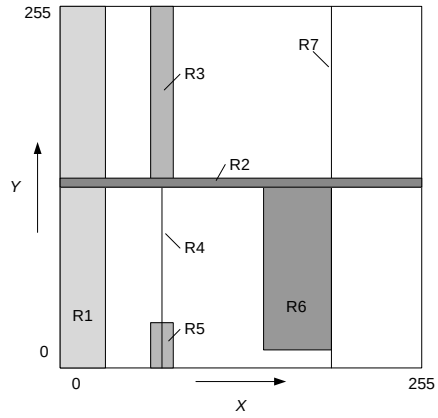



Figure 2.4: Geometrical representation of seven filters.

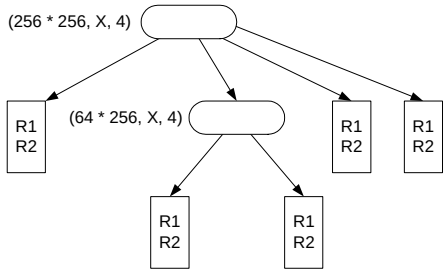



Figure 2.5: A possible tree for filters in Figure 2.4.

- A heuristic that chooses a suitable $np(C)$. A large value of $np(C)$ will decrease the tree's depth at the expense of increased storage.
- A heuristic that chooses the dimension to cut along at each internal node.
- A heuristic that maximizes the reuse of child nodes.
- A heuristic that eliminates redundancies in the tree.

All these heuristics are combined to create the "best" decision tree for the filter database and tuning parameters for these heuristics would possibly create different trees.

Tests on this algorithm use two-dimensional filter database created from publicly available routing tables. For higher dimensions classification, tests are performed using filter database obtained from ISP (Internet Service Provider) and enterprise networks. The numbers of filters in those databases are between 100 and 1,733.

The results of the tests showed that HiCuts algorithm performed well on the available filter database. Worst case search was only 20 memory accesses (200 ns for 10ns SDRAM memory). The memory requirement was small compared to its theoretical worst case. It is

important to consider the preprocessing time for this algorithm. The worst preprocessing time was 50 seconds on Pentium-II 333-MHz for a database containing less than 1,000 filters.

### 2.2.3 Tuple Space Search

Another packet classification scheme that uses hashing is *Tuple Space Search* [6]. This research is motivated by the observation that while filter databases contain many different prefixes or ranges the number of distinct *prefix lengths* tends to be small. This observation is backed by empirical study of some industrial firewall database. Knowing this, Srinivasan et.al [6] defined a tuple for each combination of field length and called the resulting set *tuple space*. Each tuple has a known set of bits in each field, therefore we can create a hash key by concatenating these bits in order , which can then be used to map filters of that tuple into a hash table.

Tuple Space Search (TSS) is a general packet classification, however the research focused on 5-dimensional filters for the experiments: IP source, IP destination, protocol type, source port number, and destination port number.

TSS defines a tuple $T$ as a vector of $K$ lengths, $K$ is the number of fields for filtering. For example, [8, 16, 8, 0, 16] is a 5-dimensional tuple, whose IP source field is an 8-bit prefix, IP destination field is a 16-bit prefix, and so on. A filter $F$ *belongs* or *maps* to tuple $T$ if the $i$th field of $F$ is specified to exactly $T[i]$ bits. For example, 2-dimensional filters $F_1 = (01*, 111*)$ and $F_2 = (11*, 010*)$ both map to the tuple [2, 3].

Tuples require every fields of a filter to be specified as a *length*. While IP addresses are always specified using prefixes, port numbers are not. Port numbers are usually specified using ranges, e.g. [0, 1024]. TSS gets around this requirement by using *nesting level* and *RangeId* each to simulate *prefix length* and *prefix* of IP addresses. For example, we have three ranges: $F_1 = [0, 65535]$, $F_2 = [0, 1023]$, and $F_3 = [1024, 65535]$. $F_1$ has nesting level of 0 and RangeId of 0. $F_2$ and $F_3$ are nested from $F_1$, thus their nesting level is 1, and they receive RangeId of 0 and 1, respectively.

With the get around explained above, each filter can now be mapped to a particular tuple $T$ in a hash table $Hashtable(T)$ with the concatenated $prefix$-es and $RangeId$-es as its hash key. Probing a tuple $T$ involves concatenating the required number of bits from the packet $P$ as specified by $T$ and then doing a hash in $Hashtable(T)$.

Searching for a matched filter for a given packet $P$ is performed by linearly probes all the tuple in the tuple set. If more than one matching filters were found, TSS picks the least cost filter. The search cost is proportional to $m$, *the number of distinct tuples*, which can be up to $N$, the number of filters in database. However, the previous observation showed that $N$ tends to be much larger than $m$. Update cost (inserting and deleting a filter) for tuple space search is also small, only one hash access. Thus, we can say that tuple space search performs much better than linear search.

Srinivasan et.al. [6] shows several improvements for the basic tuple space search. Two of them are summarized next: *Tuple Pruning* and *Rectangle Search*.

*Tuple Pruning* is motivated by the observation that in real filter databases there seem to be very few *prefixes of a given address*. For example, in Mae-East prefix database there is no address $D$ has more than 6 matching prefixes. If a 2-dimensional filter is formed from that database, then if we first find the longest destination match and the longest source match, there are only at most 6 x 6 = 36 possible tuples that are compatible with the individual

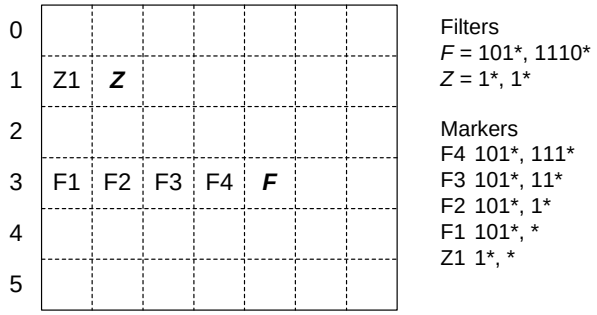



Figure 2.6: Illustration of markers and precomputation.

destination and source matches. This is very small compared to the maximum number of possible tuples for IP source-destination pair, which is 36 x 36 = 1024.

For instance, consider a 2-dimensional filter database for source $S$ and destination $D$ addresses. Suppose $D = 1010*$, and all the filters whose destination is a prefix of $D$ belong to tuples [1, 4], [1, 1], and [2, 3]. Then, the tuple list of $D$ contains these 3 tuples. Similarly, suppose $S = 0010*$, and all filters whose source is a prefix of $S$ belong to tuples [2, 4], [1, 1], and [2, 5].

Searching for the matching filter for a packet $P$ computes the longest matching prefix $PD$ and $PS$ for destination and source addresses of $P$. The next step is to take the tuple lists stored with $PD$ and $PS$, find their common intersection, and probe into that intersection. If $PD = D$ and $PS = S$ as above, the intersection list only includes [1, 1], thus we only probe into one tuple.

*Rectangle Search* is an improvement from the basic tuple space search for 2-D filter database. Rectangle Search works to cut the search time by using precomputation and markers. Search time is now down from $W^2$ hash accesses of basic tuple space search into $2W$ accesses, $W$ is the bit width of address. [6] also shows that this algorithm is optimal for 2-D filter database.

When a filter is added to the database, it leaves a marker at all the tuples to its left in its row. So a filter in the tuple $[i, j]$ leaves a marker in tuples $[i, j-1]$, $[i, j-3]$, ..., $[i, 1]$. Each filter (or marker) also precomputes the least cost filter matching it from among the tuples above it in its column. That is, a filter (or marker) in tuple $[i, j]$ precomputes the least cost filter matching it from the tuples $[i-1, j]$, $[i-2, j]$, ..., $[1, j]$. This is the marking and precomputation strategy for rectangle search.

Figure 2.6 shows an example of precomputation and markers, using two filters $F$ and $Z$. The marker $F_2$ precomputes the best matching filter among the entries in the column above it, which in this example is $Z$.

The search strategy for this algorithm starts by probing the lower-left tuple, namely, [W, 1]. At each tuple, if the probe returns a match, the search moves to the next tuple in the right. If there is no match, the search moves up one row in the same column (Figure 2.7). When a match is found, it is an indication that there is a filter on the right of the current tuple, thus it is not necessary to probe into the tuples above the current one. However, in case of no match, then there is no filter in the tuples on the right, therefore the search

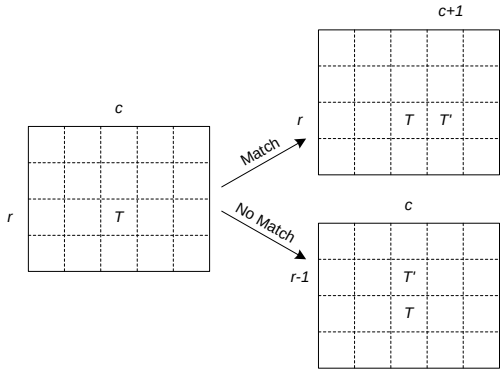



Figure 2.7: Illustration of search strategy.

can eliminate the tuples on that row. The search terminates when we reach the rightmost column or the first row.

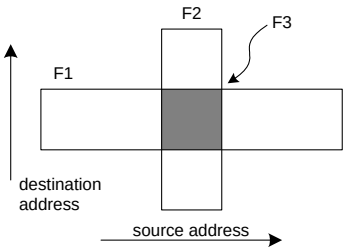
This strategy requires at most $2W - 1$ probes since there are $W$ rows and $W$ columns and requires $O(NW)$ memory. However, if we want to trade speed with memory, we can get $O(N\sqrt{W})$ memory for for $3W$ number of hash accesses in the worst case.

### 2.2.4 Fast 2D Classification for Conflict-Free Filters

Warkhede, et.al. [9] shows that for two-dimensional filter database, the search speed can be improved to $O(\log^2 W)$ in the worst case if there is no conflicting filter in the filter database.

Warkhede et.al. define the best matching filter for a packet $P$ as the matching filter that is not less specific than any other matching filter. This definition differs than the one in section 2.1 that uses filter index number as the tie-breaking mechanism.

Let filters $F_1$ and $F_2$ are two matching filters for packet $P$. The two filters *conflict* if some fields of $F_1$ are more specifics, i.e. have longer prefix, than $F_2$. Figure 2.8 shows an example two conflicting filters. In this case, the classification faces *ambiguity* because none of the two filters meets the definition of the best matching filter. To eliminate ambiguity, the classification uses *conflict resolution filters* proposed by Hari et.al. [4] that introduces a new filter that covers the conflicting area of the filters ($F_3$ in Figure 2.8).




| Filter | Source Prefix | Destination |
|---|---|---|
| F1 | 10* | 0101* |
| F2 | 1011* | 01* |
| F3 | 1011* | 0101* |

Figure 2.8: Two conflicting filters.

After resolving filter conflicts, this algorithm maps each filter to its tuple space and stored in a hash table. Each filter can create markers in the same row to its left, which is similar to [6]. In order to perform binary search on column, one half of the tuple space has to be eliminated at a time. If the hash probe returns no match, we can eliminate the entire right half of tuple space. On the other hand, if there is a match, then the entire left half of tuple space can be eliminated. This elimination is possible because there is no conflicting filter in database. Thus, we can do binary search on columns. If we do linear search on the rows, then hash probe would take $O(W \log W)$ in the worst case and it requires $O(NW \log W)$ memory.

All filters in the same column have the same prefix length on one dimension. If we concatenate this prefix with the prefix of the other dimension, then we can determine whether there is a matching filter in the column by using *best matching prefix lookup*. If using [8], then only $O(\log W)$ hash probes are required for each column search. Thus, search is now $O(\log^2 W)$ and requires $O(N \log^2 W)$ memory.

Table 2.1 compares the complexities of several two-dimensional packet classification schemes.

Table 2.1: Comparison of worst-case lookup time and space complexities for 2-D packet classification.

| Scheme | Lookup time | Memory usage |
|---|---|---|
| Tuple space search | $O(W^2)$ | $O(N)$ |
| Rectangle search | $O(W)$ | $O(NW)$ |
| Pruned tuple space | $O(W^2)$ | $O(N)$ |
| Grid of tries | $O(W)$ | $O(NW)$ |
| Cross-producting | $O(\log W)$ | $O(N^2)$ |
| Fast-2D | $O(\log^2 W)$ | $O(N \log^2 W)$ |

# Chapter 3

# 2D Packet Classification Scheme

As stated in the Chapter 1, two-dimensional packet classification for source and destination IP addresses is important because of the expected expansion of the Internet and the IP address usage. This expansion would lead to large filter databases to be installed in many routers. At the same time, routers need to process incoming packets faster than the line speed of their interfaces. This is the objective of any packet classification schemes, including the algorithm that will be described in this chapter: to do faster packet classification for larger filter database.

This chapter explains a scheme to perform two-dimensional packet classification. The basic idea of our scheme is to create many search planes and store filters in search planes. Using this idea, we can have a fast packet classification while reducing the probability of memory explosion.

## 3.1 Binary Search of Prefixes on Multiple Fields

The *Scalable High Speed IP Routing Lookup* [8] results in a logarithmic scale of the address bit width, $O(\log W)$, for routing lookup, which is a one-dimensional packet classification. The result is considerably fast, it requires only 5 hash accesses for IPv4 address, compared to 32 memory accesses when using *radix trie*. If we use perfect hash algorithm, then one hash access requires only one memory access, thus [8] is more than 6 times faster than radix trie.

The result makes it tempting to apply the algorithm to perform packet classification on more than single fields. It would make the search complexity to be $O(d \log W)$, where $d$ is the number of fields for classification. However, the algorithm would require $O(N^d)$ memory in the worst case and would easily reach that worst case.

Consider an example of a 2D packet classification using this algorithm. To find the best matching filter for a packet $P$ using [8], we have to perform the algorithm twice: search for the best matching prefix (BMP) on the source address, $BMP_{src}$, then search for the BMP on the destination address, $BMP_{dst}$, based on the value of $BMP_{src}$. One way to do this is by concatenating $BMP_{src}$ to the destination prefix to search for $BMP_{dst}$, similar to the one performed by [9]. The result of this search is the best matching filter for packet $P$ and we can get it in $O(2 \log W)$ time.

Suppose we have a 2D filter database. We first store an entry, *srcpref*, in $HashTable(src)$

for each filter, based on the source prefix of that filter. One can see that an entry might represent more than one filter. For example, we have two filters $F1 = (S_1, D_1)$ and $F2 = (S_2, D_2)$. If $S_1$ is a prefix of $S_2$, i.e. $S_1 = S_2 \cdot A$, where "$\cdot$" is a concatenation operation, then entry $S_2$ represents $F2$ only, and entry $S_1$ represents $F1$ and $F1$. Then we store the entries of all filters represented by each *srcpref* in $HashTable(dst)$ based on filter's destination prefix. Therefore, the memory requirement for this 2D packet classification is $O(N^2)$. Note that we also have to put markers for each entry as the original scheme for routing lookup.

Figure 3.1 shows an example of this algorithm for two filters $F1 = (101*, 0101*)$ and $F1 = (1011*, 10*)$. From this example, we can see that different search order, *src*-then-*dst* or *dst*-then-*src*, can result in different memory requirement. We can do a simple heuristic to reduce memory requirement, however it is not clear how much reduction we can achieve by doing it.

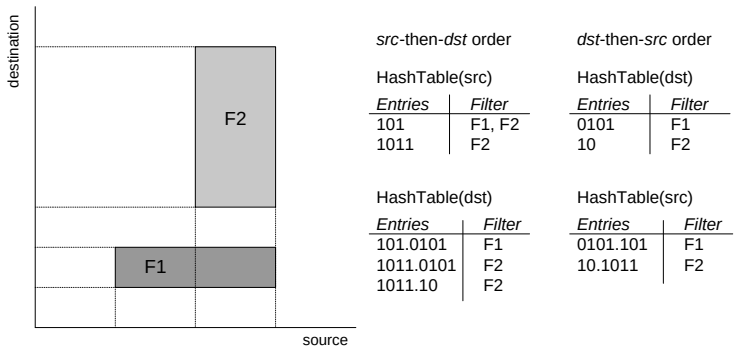



Figure 3.1: Entries for 2D filters using [8] algorithm.

## 3.2 Searching on Multiple Planes

The above scheme has a high possibility to reach the worst case $O(N^2)$ memory even though it has a considerably fast search time. The problem on this scheme is how to reduce memory requirement while keeping the $O(\log W)$ search time. This section explains a scheme trying to solve that problem.

The scheme explained in Section 3.1 can be thought as searching for a filter in a single 2D plane. We see that addition of a filter into a database of $N$ filters might require us to insert that filter $N$ times into the data structure, because *all filters lie in a single plane.* We can reduce this possibility by having *multiple planes* to store filters. When there are multiple planes, the search scheme now has to search for a plane that contains the best matching filter, then perform the scheme of previous section. This is the basic idea of this thesis.

In a geometrical visualization, a 2D filter takes the form of a rectangle sized $l \times w$. We can create a search plane for a filter as a square whose sides' $s$ length is same as the length $l$ of the rectangle and both shorter sides of the rectangle touches the sides of the square. Figure 3.2 shows the visualization of a 2D filter and its search plane.

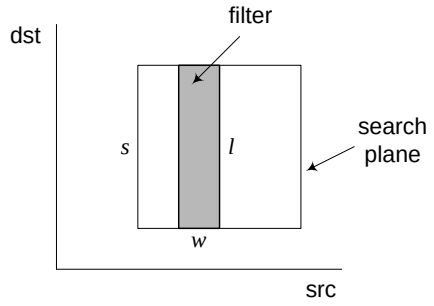



Figure 3.2: A 2D filter and its search plane.

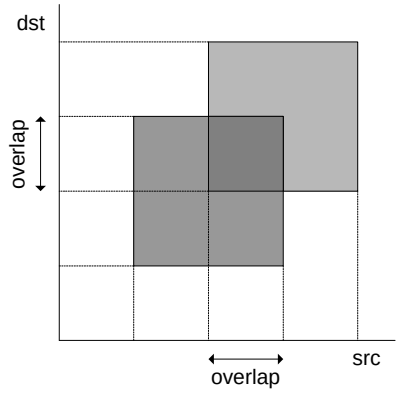



Figure 3.3: Filter overlap is not possible for prefix form fields.

This thesis assumes that fields of a 2D filter can be in prefix form only. This assumption leads to these properties of filters:

- projection of filters in any dimension cannot overlap (Figure 3.3).
- a filter, when projected in any dimension, can only covers, be covered, or be disjoint with another filter.

The latter property is a collorary to the first one. The prefix-form-only assumption makes it easy to define search planes so there can only be one *possible* search plane for a filter, as explained in the next section.

## 3.3 Filter Search Plane

A search plane of a filter, we call *filter search plane* $FSP$, is a *square* created by taking the shortest prefix length of the filters' fields. We form a square using prefixes of the filter and that shortest prefix length. This square will be the search plane for any filter that crosses it and for any filter that covers it. Thus, there can be one search plane for several filters and

a filter can be stored in several planes. Next we have the formal definition of search plane for a filter, and filters that can be contained in a search plane.

Before we proceed, first we define some notations. For a filter $F = (P_{src}/L_{src}, P_{dst}/L_{dst})$, where $P_{dim}$ and $L_{dim}$ represent the prefix and prefix length of filter $F$ in dimension $dim$ :

1. $P \otimes L$ is the prefix of $P$ when using $L$ as the prefix length.
   For example, 010110* $\otimes$ 3 = 010*.
2. $src(F) = (P_{src}/L_{src})$ is the projection of $F$ on source dimension
3. $dst(F) = (P_{dst}/L_{dst})$ is the projection of $F$ on destination dimension
4. $ldim(F)$ and $wdim(F)$ is the dimension of the length and width of rectangle $F$
5. $Lfsp(F)$ is the prefix length of $ldim(F)$, i.e. $\min(L_{src}, L_{dst})$

We can define a search plane as follows. Consider a 2D filter $F = (P_{src}/L_{src}, P_{dst}/L_{dst})$. The search plane for filter $F$ is

$$FSP(F) \doteq (P_{src} \otimes Lfsp(F)/Lfsp(F), P_{dst} \otimes Lfsp(F)/Lfsp(F)).$$

This definition creates a search plane for a filter, and since we can view the search plane as a filter with prefix form, search planes cannot overlap.

Suppose we have a search plane $SP = (PP_{src}/LP_{fsp}, PP_{dst}/LP_{fsp})$ and a filter $F = (PF_{src}/LF_{src}, PF_{dst}/LF_{dst})$. $SP$ contains $F$ if and only if:

1. $SP$ is the search plane of $F$, i.e. $SP = FSP(F)$, or
2. $F$ crosses $SP$, or
3. $F$ covers $SP$.

Writing the above conditions formally, $SP$ contains $F$ if and only if:

$$LF_{ldim(F)} \leq LP_{fsp} \quad \text{and}$$

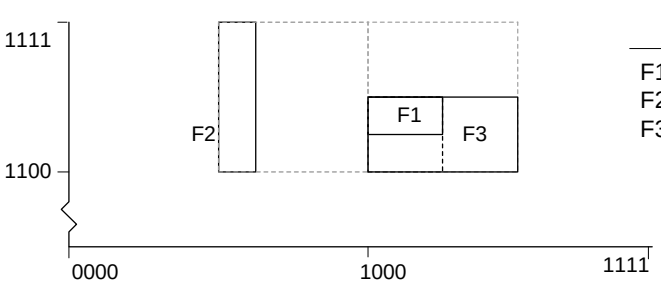
$$PP_{ldim(F)} \otimes LF_{ldim(F)} = PF_{ldim(F)} \quad \text{and}$$

$$PP_{wdim(F)} \otimes LF_{wdim(F)} = PF_{wdim(F)} \quad \text{if} \quad LF_{wdim(F)} \leq LP_{fsp} \quad \text{or}$$

$$PF_{wdim(F)} \otimes LP_{fsp} = PP_{wdim(F)} \quad \text{if} \quad LF_{wdim(F)} > LP_{fsp}.$$

As an example we have three filters, $F1 = (101*, 1101*)$, $F2 = (0100*, 11*)$, and $F3 = (10*, 110*)$. The search planes are $FSP(F1) = (101*, 110*)$, $FSP(F2) = (01*, 11*)$, and $FSP(F3) = (10*, 11*)$ (see Figure 3.4). We have three FSPs and a total of four filters contained in all FSPs, as shown in Table 3.1. From Figure 3.4 and Table 3.1 we note that:

- The square of $FSP(F1)$ is inside of the square of $FSP(F3)$, however both are different planes.
- $F3$ covers $FSP(F1)$, thus it is contained in that FSP.




| Filter | Search Plane |
|---|---|
| F1 (101*, 1101*) | (101*, 110*) |
| F2 (0100*, 11*) | (01*, 11*) |
| F3 (10*, 110*) | (10*, 11*) |

Figure 3.4: Three filters and search planes.

Table 3.1: FSP and its contained filters of Figure 3.4.

| FSP | Contained filters |
|---|---|
| $FSP(F1)$ | $F1$, $F3$ |
| $FSP(F2)$ | $F2$ |
| $FSP(F3)$ | $F3$ |

- While $F1$ is in the square of $FSP(F3)$, $F1$ is not contained in that FSP because $F1$ *doesn't cross or cover* $FSP(F3)$

We see in Table 3.1, $FSP(F1)$ stores $F1$ and $F3$. This is an example where multiple search planes can result in $O(N^2)$ memory requirement. We are interested to know in what cases our multiple search plane scheme would lead to that result, i.e. a filter appears in more than one FSP. Figure 3.5 shows several cases of FSP when there are two filters, namely $F1$ and $F2$. Filter $Fn$ is defined as $(Pn_{src}/Ln_{src}, Pn_{dst}/Ln_{dst})$.

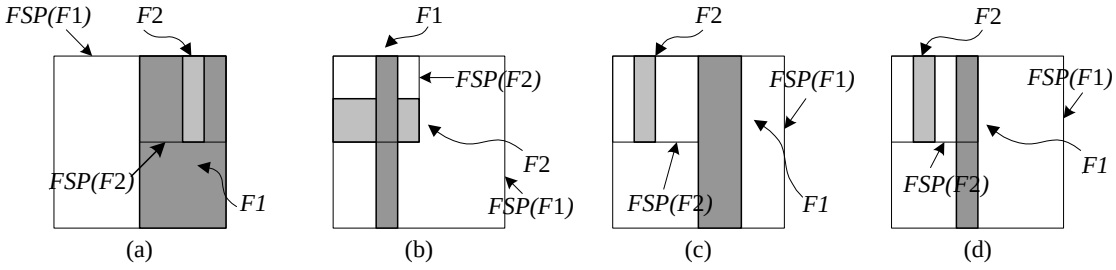



Figure 3.5: Cases of FSP of two filters.

Figure 3.5 (a) is a case where $F1$ covers $F2$, and Figure 3.5 (b) is a case where $F1$ and $F2$ conflict. These are two obvious cases where $FSP(F2)$ contains both $F2$ and $F1$, thus $F1$ appears in two FSPs. However, for Figure 3.5 (b), if $Lfsp(F1) = Lfsp(F2)$, then $FSP(F1) = FSP(F2)$, which means both filters appear only in one FSP. This is a special case of conflicting filters.

Figure 3.5 (c) and (d) show two different cases of filter arrangements. These cases are neither a conflicting filters nor a filter covers the other. The difference between these cases is in Figure 3.5 (d), filter $F1$ crosses $FSP(F2)$, which is not the case for Figure 3.5 (c). Thus, in Figure 3.5 (d), $F1$ appears twice. We cannot easily infer that case (d) happens just by looking at the lines of filter definition in filter database.

Here we have a formal definition of this case. Consider two filters $F1$ and $F2$ as in Figure 3.5. If $F1$ is a prefix of $F2$ on one dimension, and $F1$ is neither covering $F2$ nor in conflict with $F2$, $FSP(F2)$ contains $F1$ if

$$ldim(F1) = ldim(F2) = ldim \qquad \text{and} \qquad L1_{ldim} < L2_{ldim}$$

$$\text{and} \qquad P2_{wdim} \otimes L2_{ldim} \quad \text{is a prefix of} \quad P1_{wdim}.$$

With this formal definition, we can notice the case of Figure 3.5 (d) easier.

Table 3.2: Filter database to show the case of Figure 3.5 (d).

| Filter | Definition |
|---|---|
| $F1$ | $(10*, 11010*)$ |
| $F2$ | $(101*, 11001*)$ |
| $F3$ | $(101*, 011010*)$ |

Table 3.2 is an example to illustrate the (d) case. As we see in that table, source dimension definition of $F1$ is a prefix of that of $F2$ and $F3$. Remembering the formal definition above, we can infer right away that $FSP(F2)$ contains $F1$ because 11001* $\otimes$ 3 is a prefix of 11010*, and $FSP(F3)$, on the other hand, doesn't contain $F1$.

## 3.4 Algorithm to Search for FSP

The previous section defines and explains the filter search plane. Because of its definition, an FSP can be considered as a 2D filter, thus we can search for an FSP using any available packet classification algorithm. The objective of any packet classification is to find the best matching filter (BMF) for a packet. Our scheme stores filters in search planes, and to find BMF, we use two-step process:

1. search for the FSP containing BMF, then
2. search for BMF within the FSP.

However, a filter – including the best matching filter – can be stored in more than one FSPs, thus FSP containing the BMF might not be unique. Before we can search for the FSP containing BMF, we have to define which FSP is the best FSP containing BMF, which is the objective of this search procedure.

Suppose that $Fm$ is the BMF for packet $P = (S, D)$, then $FSP(Fm)$ contains $Fm$, thus searching for the BMF for $P$ in $FSP(Fm)$ would produce a result. Let's also suppose that there are other search planes $FSPi$ containing $Fm$. However, FSPs that are relevant

to packet $P$ are only $FSP_{p,l} = (S \otimes l/l, D \otimes l/l)$, $l \leq W$. Therefore, FSPs containing $Fm$ relevant to $P$ are $FSP_{p,l} \cap FSP_i$, and we can define that the best FSP containing BMF among them is the one that has the longest prefix. This definition enables us to search for FSP similar to searching for BMF in FSP, as we will see later.

A property of an FSP is FSP has the same prefix length for its source and destination address definitions. If we use the point of view of *Tuple Space Search* [6], then FSP is always located in the $(l, l)$ tuple space, where $l$ is the prefix length of FSP, and we can apply that scheme to find the FSP that contains the best matching filter. Thus, the worst-case search time for an FSP is $O(W)$ hash accesses, where $W$ is the bit-width of address space.

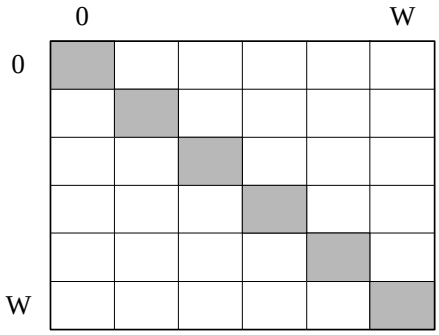



Figure 3.6: FSPs occupy a diagonal of 2D Tuple Space.

Figure 3.6 shows the visualization of FSPs in 2D Tuple Space. FSPs of a filter database only occupy a diagonal in visualization, so we can search FSPs as if FSPs are one-dimensional filters. We can speed up the search by using *binary search on prefix length* with a little modification, so we have the worst case of $O(\log W)$.

Consider a 2D filter database of $N$ filter search planes $FSP\text{i} = (S\text{i}/L\text{i}, D\text{i}/L\text{i})$, $1 \leq i \leq N$. We map $FSP\text{i}$ into tuple space $L\text{i}$ and store it in $HashTable(L\text{i})$ that corresponds to that tuple space with $(S\text{i}, D\text{i})$ as the key. After storing all FSPs, now for each $FSP\text{i}$ we can store a marker at each $HashTable(T)$, $T < L\text{i}$, using $(S\text{i} \otimes T, D\text{i} \otimes T)$ as the key. Storing markers for $N$ filter search planes requires $O(WN)$ time and $O(WN)$ memory.

Each marker $M$ points to the best matching FSP of that marker, $M.bmsp$. We store markers for $FSP\text{i}$ by moving forwards from 0 to $L\text{i}$. At each $T$, $T \leq L\text{i}$, we create a hash key for the marker and probe $HashTable(T)$ to know whether there is already an FSP associated with marker's key. We only store a marker in a hash table if there is no FSP associated with the marker's key in that hash table. If we find an FSP, we record the FSP as the best matching FSP in the subsequent markers. This marking strategy is shown in Algorithm 1. Given the marking strategy, whenever we probe $HashTable(i)$ and we do not find a marker, we can be sure that there is no FSP on $j > i$.

To find the best FSP containing BMF, we start to probe at the median of $W$, which is on the center of tuple space of Figure 3.6, and we use binary search on these hash tables. If a probe on a $HashTable(T)$ doesn't return a match, we can eliminate the lower-right elements of $T$ in the diagonal. If we have a match, we can eliminate the upper-left ones. Finding a match, we move to probe the median of the lower right half of the diagonal of $T$,

**Algorithm 1** Storing markers of $FSP$

**Require:** all FSPs stored in hash tables
  **for all** $i$ such that $1 \leq i \leq N$ **do**
    $j \Leftarrow 0$
    $M.bmsp \Leftarrow NULL$
    **while** $j < L\text{i}$ **do**
      $HashKey \Leftarrow (S\text{i} \otimes j, D\text{i} \otimes j)$
      $HashEntry \Leftarrow$ probe $HashTable(j)$ using key $HashKey$
      **if** $HashEntry$ is an FSP **then**
        $M.bmsp \Leftarrow HashEntry$
      **else**
        insert marker $M$ into $HashTable(j)$ using key $HashKey$
      **end if**
      $j \Leftarrow j + 1$
    **end while**
  **end for**

**Algorithm 2** Binary search to find the $FSP$ containing the best matching filter.

**Require:** Packet $P(S, D)$
  $FSP \Leftarrow 0$
  $MinProbe \Leftarrow 0$
  $MaxProbe \Leftarrow W$
  $CurProbe \Leftarrow$ median of $MinProbe$ and $MaxProbe$
  **while** $MinProbe \leq MaxProbe$ **do**
    $HashKey \Leftarrow (S \otimes CurProbe, D \otimes CurProbe)$
    $M \Leftarrow$ probe $HashTable(CurProbe)$ using key $HashKey$
    **if** $M$ exists **then**
      $FSP \Leftarrow M.bmsp$
      $MinProbe \Leftarrow CurProbe$
    **else**
      $MaxProbe \Leftarrow CurProbe$
    **end if**
    $CurProbe \Leftarrow$ median of $MinProbe$ and $MaxProbe$
  **end while**

otherwise we proceed to probe the median of the upper-left-half one, until we find the best FSP.

Whenever we have a match $M$, we record $M.bmsp$. If we face failures during the binary search after recording $M.bmsp$, we use it as the result of our search. The search algorithm for FSP is shown in Algorithm 2. This search algorithm requires only $O(\log W)$ hash accesses in the worst case.

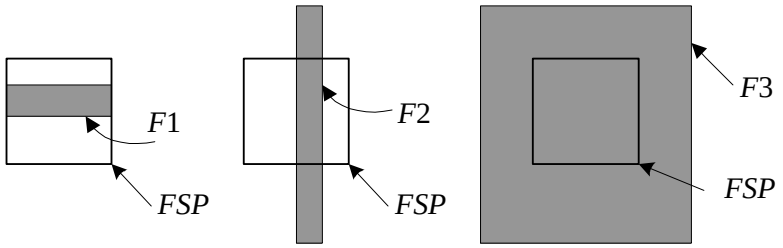



Figure 3.7: Filters that can be stored in an FSP.

## 3.5 Searching for Filters in an FSP

After finding the best FSP for packet $P$, our scheme needs to find the BMF of $P$ within the FSP. The definition of FSP says that an FSP contains only filters that cross or contain the FSP. As a collorary to the definition, if a filter $F$ is stored in a filter search plane $FSP$, then the shortest prefix length of $F$ must be less than or equal to the prefix length of $FSP$. Figure 3.7 illustrates the cases that conform to the definition.

Figure 3.7 shows that if a search plane $FSP$ contains a filter $F$, projection of $F$ on one dimension *must* covers or coincides with the projection of $FSP$ on that dimension. This is a property of filters in an FSP. This property simplifies the search for a 2D filter into one-dimensional packet classification because we can project all filters in an FSP to one dimension only and do best matching prefix search on that dimension. If a filter coincides or covers both dimension of FSP, we can pick any dimension. If it doesn't, we project the filter to the dimension where it neither covers nor coincides the FSP. For filters in Figure 3.7, we project $F1$ to destination dimension (vertical axis), $F2$ to source dimension (horizontal axis), and we can project $F3$ to any dimension.

Algorithm 3 shows how to project and store filters of an FSP, and compute and store markers of each filter. The algorithm to store markers of a filter is similar to Algorithm 1, thus it is not shown in detail. In this algorithm, filters like $F3$ in Figure 3.7 are projected to source dimension. Due to the property of filters in FSPs, we only need to store each filter once, instead of – possibly – many times as in the case of Section 3.1. The cost of storing $N$ filters and their markers in an FSP in $O(WN)$ time with the memory requirement of $O(WN)$.

Searching for the best matching filter (BMF) in FSP requires us to perform two one-dimensional best matching prefix (BMP) searches: one in source dimension, and one in destination dimension. We compare the BMP of each dimension to find the BMF. We can also use binary search for this purpose since we have the same marking strategy as marking to search for FSP (Section 3.4). This algorithm (see Algorithm 4) requires $2 \log W$ hash accesses in the worst case. `bmpsearch`(*point*, *hash*) is a function that returns the filter of the best matching prefix of *point* in hash table *hash*. Algorithm 4 doesn't show the details of `bmpsearch` algorithm, since it is similar to Algorithm 2.

**Algorithm 3** Storing filters in an FSP.

**Require:** $F\text{i} = (PF\text{i}_{src}/LF\text{i}_{src}, PF\text{i}_{dst}/LF\text{i}_{dst})$
**Require:** $FSP = (PP_{src}/LP, PP_{dst}/LP)$
  **for all** $F\text{i}$ **do**
    $LenSrc \Leftarrow \max(LF\text{i}_{src}, LP)$
    $LenDst \Leftarrow \max(LF\text{i}_{dst}, LP)$
    **if** $LenDst > LenSrc$ **then**
      $HashKey \Leftarrow (PF\text{i}_{dst}, LF\text{i}_{dst})$
      insert filter $F\text{i}$ into $HashDst(FSP)$ using key $HashKey$
    **else**
      $HashKey \Leftarrow (PF\text{i}_{src}, LF\text{i}_{src})$
      insert filter $F\text{i}$ into $HashSrc(FSP)$ using key $HashKey$
    **end if**
  **end for**
  **for all** filter entries in $HashDst(FSP)$ **do**
    compute and store markers
  **end for**
  **for all** filter entries in $HashSrc(FSP)$ **do**
    compute and store markers
  **end for**

**Algorithm 4** Searching for the BMF of a packet.

**Require:** $P = (S, D)$
**Require:** $FSP = (PP_{src}/LP, PP_{dst}/LP)$
  $BMFsrc \Leftarrow$ `bmpsearch`$(S, HashSrc(FSP))$
  $BMFdst \Leftarrow$ `bmpsearch`$(D, HashDst(FSP))$
  **if** $BMFsrc$ is better than $BMFdst$ **then**
    $BMF \Leftarrow BMFsrc$
  **else**
    $BMF \Leftarrow BMFdst$
  **end if**

## 3.6 Storing Filters in a Search Plane

So far we have discussed about creating search planes, searching the best search plane for a packet, and searching the best matching filter for a packet in a search plane. This section explains an algorithm to store filters in search planes.

Assuming that we have already created FSP of all filters, the most naïve way to store filters in FSPs is testing each filter to all FSPs to find out whether the filter has to be stored in the FSP or not. This algorithm requires $N$ comparisons for each FSP to find all filters that must be stored in the FSP.

We can detect all those filter faster by the observation explained below. Suppose a filter $F_l = (P_{src}/L_{src}, P_{dst}/L_{dst})$ has to be stored in a search plane $FSP(F_s) = (PP_{src}/LP, PP_{dst}/LP)$, and $FSP(F_l) \neq FSP(F_s)$. It means that $FSP(F_l)$ *must* cover$FSP(F_s)$. If we search for filters in all FSPs that cover $FSP(F_s)$, we can find *all* filters that must be stored in $FSP(F_s)$.

We need to visit at most $W$ FSPs to do this.

When we visit an FSP to find filters to be stored $FSP(F_s)$, we will have two cases like $F2$ and $F3$ in Figure 3.7. Case of $F2$ is where the projection of $FSP(F_s)$ to one dimension covers the filter's projection. Case of $F3$ is the opposite, filter's projection covers or matches the projection of $FSP(F_s)$. To find $F3$, we can expand $FSP(F_s)$ until $FSP(F_s) = FSP(F_l)$. At each expansion of $FSP(F_s)$, we detect whether its projection in any dimension matches the projection of some filters by probing $HashSrc(FSP(F_l))$ and $HashDst(FSP(F_l))$. This algorithm requires at most $2W$ hash accesses to detect and include all filters to $FSP(F_s)$ filter list.

For example, we have two FSPs, $FSP_m = (10*, 01*)$ and $FSP_n = (1001*, 0110*)$, and two filters $F1 = (10*, 011*)$ and $F2 = (10101*, 01*)$. We expand $FSP_n$ until it matches $FSP_m$: $FSP'_n = (100*, 011*)$, $FSP''_n = (10*, 01*)$. At $FSP'_n$ level, we probe $HashSrc(FSP_m)$ using $100*$ as the key. This probing returns nothing. We then probe $HashDst(FSP_m)$ using key $011*$ and it returns the hash entry for filter $F1$. We do the same thing at $FSP''_n$ level and probings return nothing.

Figure 3.8 illustrates the expansion of $FSP_n$. In figure (b), this process finds $F1$, thus store it in the filter list of $FSP_n$. In figure (a) and (c), this expansion doesn't find any filters.

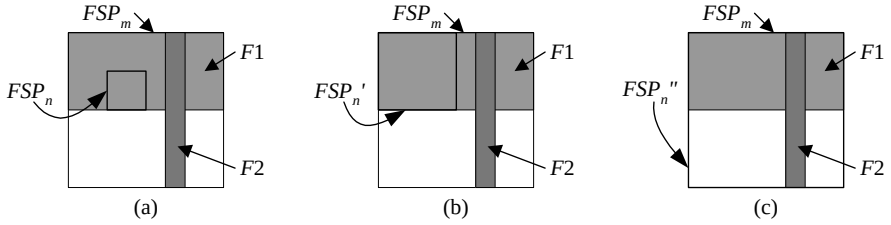



Figure 3.8: Expanding $FSP_n$ in $FSP_m$ to find filters.

When trying to find filters like the case of $F2$ in Figure 3.7, remember the marking strategy for filters in search plane as explained in Section 3.5. We can test whether there are filters that have to be stored in $FSP(F_s)$ by probing $HashSrc(FSP(F_l))$ and $HashDst(FSP(F_l))$ using the source and destination definition of $FSP(F_s)$, respectively, to create the hash keys. If probing resulted nothing, then there is no filter that we have to store in $FSP(F_s)$. If probing matches a marker, we follow the marker down until we find the filter(s) that create(s) the marker.

The procedure above has to probe at most $2W$ times until it finds the hash entry for a filter. Whenever probing at prefix length $l$ finds a marker $M_l$, there has to be at least one marker or filter at prefix length $l+1$. For example if a marker $M_l = 1010*$ exists, there has to be either $10101*$ or $10100*$, or both. The algorithm has to probe at both possibilities because it has no clue which one it has to probe at prefix length $l+1$ to get a match. Adding another variable *M.lead* in marker to lead the algorithm to probe correctly will reduce the number of probing to $W$. Algorithm 5 shows this procedure.

Combining the algorithms to visit FSPs and to find filters in FSPs, we need at most $2W^2 + WQ$ hash accesses, $W$: bit-width of address space, and $Q$: the number of filters found, for each FSP to find all filters that it has to store in its' database. Algorithm 6

displays the algorithm to store all filters of an FSP into another. The cost of this algorithm is independent of the number of filters in the database, thus it is useful for large filter databases.

## 3.7 Building the Database Structure

We now have all the necessary algorithms to build the database structure of a two-dimensional filter database to enable a two-dimensional packet classification with search time of $O(\log W)$. Before creating a complete algorithm to build the database, we have the following observation, which reduces the time cost of the algorithm.

Previous section shows an algorithm to find all filters that have to be stored in an FSP, which costs at most $2W^2+WQ$ hash accesses. This is due to the assumption that an FSP has to visit every FSPs that cover it. Suppose that we have a filter $F1$, which creates $FSP(F1)$, and two search planes $FSP_m$ and $FSP_n$; where $FSP(F1)$ covers $FSP_m$, and $FSP_m$ covers $FSP_n$. If $FSP_n$ has to store $F1$, then $FSP_m$ also has to store $F1$ (see Figure 3.9).

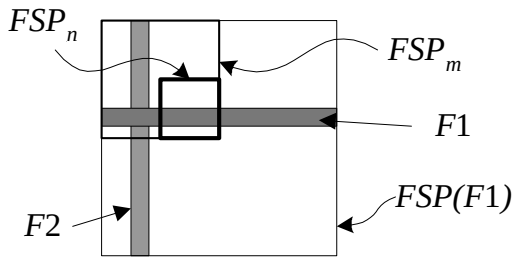



Figure 3.9: $FSP_n$ and $FSP_m$ store $F1$.

This observation means that we can reduce the time to find all filters for an FSP by processing each search plane in prefix-length order, starting from the shortest up to the longest one. For example, if we have $FSP_m = (10*, 11*)$ and $FSP_n = (101*, 110*)$, we process $FSP_m$ before process $FSP_n$. This processing order ensures that when we are processing an $FSP_i$, the smallest search plane covering $FSP_i$ *already* contains all filters that $FSP_i$ has to store, so we only have to search for the filters in one search plane. Furthermore, our marking strategy includes variable *bmsp*. If we have an $FSP_n$ whose prefix length is $l$ and we want to find the smallest FSP, $FSP_m$ covering it, probing at $l-1$ and reading its *bmsp* will lead us directly to $FSP_m$. This reduces the time to store all filters in an FSP to $1+2W+WQ$. The algorithm to build the database structure is shown in Algorithm 7.

## 3.8 Dealing with Wildcard Filter Problem

The design of our scheme is susceptible to wildcard filters, e.g. filters with wildcard prefix in any of their dimension. This is because of the definition of which filters can be stored in an FSP. Figure 3.10 shows the case of wildcard filters in filter database.

Figure 3.10 shows a filter database with 4 filters, where $F1$ is a wildcard filter whose destination dimension is the one with wildcard prefix. Let's consider the filter database if

$F1$ doesn't exist. If $F1$ doesn't exist, then each FSP in this example only stores the filter creating it. If $F1$ exists, then $FSP(F2)$, $FSP(F3)$, and $FSP(F4)$ has to store $F1$. This situation is like $F2$ and $F3$ of Figure 3.7, but in a much larger scale.

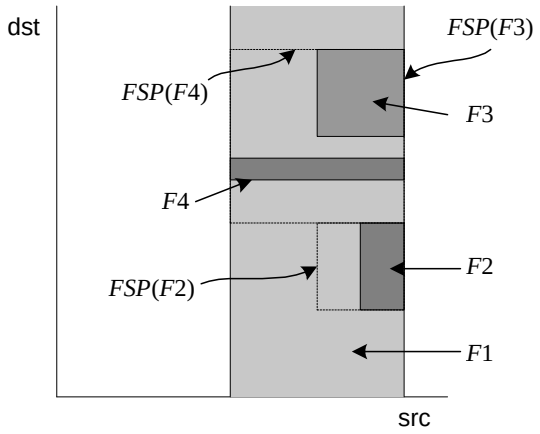



Figure 3.10: A wildcard filter in filter database.

One way to remove the effect of wildcard filters is not to store them in any FSPs except in its search plane. With this strategy, we have an additional step to find the correct best matching filter. The additional step is if the best FSP has non-zero prefix length and we fail to find the BMF in that FSP, we have to do another search for BMF in the zero prefix-length FSP. Thus, we have to do $5 \log W$ hash accesses in the worst case. This strategy is a time–space trade-off.

This strategy completes the design of a two-dimensional packet classification of this thesis. Next chapter will discuss the simulations for this scheme.

**Algorithm 5** Follow markers to find filters.

**Require:** $Prefix$ to follow; $HashTable$ storing markers
  $HashKey \Leftarrow Prefix$
  $MarkSrc \Leftarrow$ probe $HashTable$ using $HashKey$
  **if** $MarkSrc$ exists **then**
    $i \Leftarrow 0$
    $PrefChild \Leftarrow NULL$
    **loop**
      **LABEL** `Loop0:`
      $Follow[i].marker \Leftarrow MarkSrc$
      $Follow[i].visit0 \Leftarrow 0$ ; $Follow[i].visit1 \Leftarrow 0$
      **if** $MarkSrc$ is a filter **then**
        add $MarkSrc$ to $FilList$ array
      **end if**
      **if** $MarkSrc.lead$ leads to child 0 **then**
        $Follow[i].visit0 \Leftarrow 1$
      **end if**
      **if** $MarkSrc.lead$ leads to child 1 **then**
        $Follow[i].visit1 \Leftarrow 1$
      **end if**
      **LABEL** `Loop1:`
      **if** $Follow[i].visit0 = 1$ **then**
        $Follow[i].visit0 \Leftarrow 0$
        $PrefChild \Leftarrow PrefChild \cdot 0$
        $HasKey \Leftarrow Prefix \cdot PrefChild$
        $MarkSrc \Leftarrow$ probe $HashTable$ using $HashKey$
        **if** $MarkSrc$ exists **then**
          $i \Leftarrow i + 1$ ; **goto** `Loop0`
        **end if**
      **end if**
      **if** $Follow[i].visit1 = 1$ **then**
        $Follow[i].visit1 \Leftarrow 0$
        $PrefChild \Leftarrow PrefChild \cdot 1$
        $HashKey \Leftarrow Prefix \cdot PrefChild$
        $MarkSrc \Leftarrow$ probe $HashTable$ using $HashKey$
        **if** $MarkSrc$ exists **then**
          $i \Leftarrow i + 1$ ; **goto** `Loop0`
        **end if**
      **end if**
      $i \Leftarrow i - 1$
      **if** $i < 0$ **then finish**
      $PrefChild \Leftarrow PrefChild \otimes i$ ; **goto** `Loop1`
    **end loop**
  **end if**

**Algorithm 6** Find all filters in $FSP_l$ to be stored in $FSP_s$.

$FilList \Leftarrow$ `NULL` {$FilList$ is an array to store found filters}
$Llen \Leftarrow$ `fsplen`($FSP_l$) {`fsplen()` returns the prefix length of an FSP}
$Slen \Leftarrow$ `fsplen`($FSP_s$)
$i \Leftarrow Slen$
**while** $i \geq Llen$ **do**
  $i \Leftarrow i - 1$
  $FSPtest \Leftarrow FSP_s \otimes i$
  $AddFil \Leftarrow$ probe $HashSrc(FSP_l)$ using key `src`($FSPtest$) {`src()` is projection of filter/FSP in source dimension}
  **if** $AddFil$ exists **then**
    add $AddFil$ into $FilList$ array
  **end if**
**end while**
$AddFil \Leftarrow$ probe $HashDst(FSP_l)$ using key `dst`($FSPtest$) {`dst()` is projection of filter/FSP in destination dimension}
**if** $AddFil$ exists **then**
  add $AddFil$ into $FilList$ array
**end if**
$MarkSrc \Leftarrow$ probe $HashSrc(FSP_l)$ using key `src`($FSP_s$)
**if** $MarkSrc \neq$ `NULL` **then**
  follow $MarkSrc.lead$ to find filters {Algorithm 5}
  add found filters to $FilList$ array
**end if**
$MarkDst \Leftarrow$ probe $HashDst(FSP_l)$ using key `dst`($FSP_s$)
**if** $MarkSrc \neq$ `NULL` **then**
  follow $MarkDst.lead$ to find filters {Algorithm 5}
  add found filters to $FilList$ array
**end if**

**Algorithm 7** Build database structure for a filter database.

**Require:** $N$ filters, $F\text{i}, 0 \leq i < N$
  **for all** filter $Fi \quad 0 \leq i < N$ **do**
    **if** $FSP(F\text{i})$ not exists **then**
      create search plane $FSP(F\text{i})$
      store $FSP(F\text{i})$ based on prefix length order, short to long
    **end if**
    store $F\text{i}$ in $FSP(F\text{i})$ {Algorithm 3}
  **end for**
  **for all** $FSP\text{k}$ in sorted $FSP$ list, $0 \leq k < M$ **do**
    $FSPup \Leftarrow$ `NULL`
    $Len \Leftarrow$ `fsplen`$(FSP\text{k})$ {`fsplen()` returns the prefix length of an FSP}
    $Len \Leftarrow Len - 1$
    $HashKey \Leftarrow FSP\text{k} \otimes Len$
    $FSPup \Leftarrow$ probe $HashTable(Len)$ using $HashKey$
    $HashKey \Leftarrow FSP\text{k} \otimes FSPup.bmsp$
    $FSPup \Leftarrow$ probe $HashTable(FSPup.bmsp)$ using $HashKey$
    **if** $FSPup \neq$ `NULL` **then**
      $FilList \Leftarrow$ get all filters to be stored in $FSP\text{k}$ {Algorithm 6}
      store filters of $FilList$ in $FSP\text{k}$ {Algorithm 3}
    **end if**
  **end for**

# Chapter 4

# Simulation

This chapter presents the details of data structure in implementing 2D packet classification scheme of Chapter 3. This chapter doesn't give any details of the pseudo-codes of the implementation because they are based on the algorithms explained before. This chapter then explains filter database design for our simulation and presents the simulation results.

## 4.1 The Implementation Data Structure

The algorithms of our scheme are implemented in C language for simulation purpose. This section explains details of the data structure used for our packet classification scheme.

When we read a filter database, we store it as an array of filters. Using an array of filters eases random access to each filter by only using filter's index value. Each filter is stored as two tuples of prefix and prefix length pair and a number to represent its index value. Figure 4.1 shows the data structure for a filter.

Besides storing it in an array, we also have to store it, probably several times, in a hash table as a marker for filter. The data structure for a filter marker is shown in Figure 4.2. This data structure has *lead* element to be used by Algorithm 5 to store other filters in an FSP, and *bmp* to store best matching prefix. This marker also stores pointer to a filter. This element points to the memory location of a filter if it is really a marker to a filter, otherwise it contains *NULL*.

We store an FSP twice: in a linked list and in a hash table. Figure 4.3 shows the data structure used to represent an FSP. This structure stores FSP definition similar to the data

```
typedef struct filter_ {
  u_int32_t    src_prefix;
  u_int        src_preflen;
  u_int32_t    dst_prefix;
  u_int        dst_preflen;
  u_int32_t    fil_num;
} filter;
```

Figure 4.1: Data structure for a filter.

```
typedef struct fil_mark_ {
  u_int     lead, bmp;
  filter    *filter;
} fil_mark;
```

Figure 4.2: Marker for a filter.

```
typedef struct fsp_data_ {
  u_int32_t    src_prefix;
  u_int        src_preflen;
  u_int32_t    dst_prefix;
  u_int        dst_preflen;
  fsp_mark     *marker;
} fsp_data;
```

Figure 4.3: An FSP.

```
typedef struct fsp_mark_ {
  u_int     bmsp, flsize;
  filter    **flist;
} fsp_mark;
```

Figure 4.4: Marker for an FSP.

structure of a filter, since as stated in the previous chapter, an FSP is also can be viewed as a filter. This structure also stores pointer to a marker in a hash table representing this FSP.

A marker for FSP has the *bmsp* element, the best matching search plane, which is used during searching for the best FSP. A marker that represents an FSP, contains at least 1 filter. *flsize* and *flist* form the filter list of an FSP. Element *flsize* indicates how many filters are contained within the FSP. If *flsize* is not 0, then this marker represents an FSP and the contained filters can be found by looking in *flist*. *flist* is a pointer to an array of pointers to filter. We use this strategy to reduce memory usage because a filter can be stored in more than one FSP, thus it is better for an FSP to store pointers to filter instead of the filters. This data structure is shown in Figure 4.4.

The basic data structure for this scheme is *hash table*. The scheme implies that we need to have $(W + 1) + 2N$ hash tables: $W + 1$ hash tables for storing FSP entries, and 2 hash tables to store filter's projections in an FSP for each of $N$ FSPs of the filter database. However, for the ease of implementation, we only use three hash tables: one for FSPs and one for each filter projection in source and destination dimension. This is possible by including *prefix length* in the hash key of each entry and including FSP definition in case of filter entry. With this strategy, hash key for an FSP entry and a filter are a two tuples and three tuples, respectively, of prefix and prefix length pair. For example, we have a filter $(10/8, 192.168/24)$. The FSP for this filter is $(10/8, 192/8)$. Hash keys for its FSP and filter

```
typedef struct fsp_key_ {
  u_int32_t    src_prefix;
  u_int        src_preflen;
  u_int32_t    dst_prefix;
  u_int        dst_preflen;
} fsp_key;
```

Figure 4.5: Data structure of FSP hash key.

```
typedef struct fil_key_ {
  u_int32_t    src_prefix;
  u_int        src_preflen;
  u_int32_t    dst_prefix;
  u_int        dst_preflen;
  u_int32_t    fil_prefix;
  u_int        fil_preflen;
} fil_key;
```

Figure 4.6: Data structure of filter hash key.

entries are $(10/8, 192/8)$ and $(10/8, 192/8, 192.168/24)$. Figure 4.5 and Figure 4.6 show the data structure of each hash key.

## 4.2 Simulation Filter Database Design

We use simulation to evaluate the performance of our 2D packet classification scheme. Using simulation, we want to know the time to build data structure for filter databases and memory usage of our scheme. The worst-case search time of this scheme is $O(\log W)$, which is considerably fast. Memory usage, however, should receive more attention since our scheme tries to reduce the probability to reach the worst case of $O(N^2)$. In this simulation, we want to know how our scheme will perform in real-life filter databases.

To simulate this scheme, we create random and non-random two-dimensional filter databases based on the publicly available Internet routing table. Randomly creating filter databases approach is also used by [3], [7], and [10]. However, [3] and [7] do not give any detail on how to create filter databases. Creating random filter databases straight from Internet routing table would not result in filters that we can use to evaluate our scheme. Therefore we want artificial filter databases for our simulation can be used as a baseline to measure the performance of our scheme, especially for the memory requirement.

[10] attempts to model large filter databases and creates random filter databases based on that model. The basic idea is to classify network elements into distinct types, e.g. workstation hosts, server hosts, subnet border routers, enterprise core routers, enterprise edge routers, ISP edge routers, ISP core routers, and ISP peering routers. For each class, the applications and their filter tables are identified. Based this model, [10] projects that ISP edge routers class has to support the largest number of filters and enterprise edge routers

class is next.

For our simulation we choose to use *Autonomous System* (AS) as the base to create filters and routers having these filters are *AS border routers*. We choose to use Autonomous Systems because even though an AS is defined as a group of IP networks operated by one or more network operators which has a single and clearly defined external routing policy, in practice an AS usually belongs to a single ISP or enterprise. Because of this, it is likely that an Autonomous System also has a single security (firewall) and QoS policy.

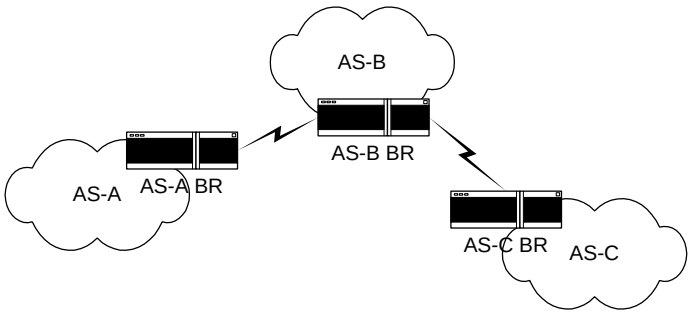



Figure 4.7: AS border routers.

We choose to simulate filter databases running on AS border routers, and we create filter databases from prefixes of two ASes. An AS border router connects an Autonomous System to another (Figure 4.7). It is the entrance and exit points for packets originated from and destined to the corresponding AS. It is usually where filter database is the most complete compared to the other filter databases in that AS. If we use the model by [10], an AS border router can be categorized as an ISP edge router or as an enterprise edge router, depending on whether the particular AS is owned by an ISP or an enterprise.

In selecting ASes for this simulation, we use the Internet routing table made available by Telstra Network, Australia [1]. This routing table consists of around 100 thousand prefixes and about 12 thousand ASes advertise those prefixes. First we separate prefixes by their originating AS number and we view prefixes of an AS as a single routing table. We process each routing table by counting the number of prefixes, maximum prefix level, duplicated prefixes and the ratio of duplicated prefixes to the number of prefixes.

Prefix level is a measure that counts the number of prefixes of a given IP address in a routing table. For example, we have a routing table consists of four entries: 10.1.1/24, 10.1/19, 10.1/16, and 10.1.224/23. For IP address 10.1.1.1 we have three prefixes, and for IP address 10.1.224.2 we have two prefixes. The maximum prefix level of our routing table is 3.

Duplicated prefixes shows the number of times prefixes are stored in other prefixes because the former cover the latter. For example, suppose we have an AS consists of 4 prefixes: $A$, $B$, $C$, and $D$. $A$ is a prefix of $B$, $B$ is a prefix of $C$, and none of $A$, $B$, $C$ is a prefix of $D$. This AS has maximum prefix level of 2 ($A$ and $B$ are prefixes of $C$) and duplicated prefixes of 3 ($A$ is stored in $B$ and $C$, and $B$ is stored in $C$).

Table 4.1: ASes for cross-product filter databases.

| AS num | Prefixes | Level | Dup. pref. | % Dup. pref. |
|---|---|---|---|---|
| 680 | 230 | 1 | 0 | 0.00% |
| 786 | 183 | 1 | 0 | 0.00% |
| 1913 | 124 | 1 | 0 | 0.00% |
| 4713 | 117 | 1 | 0 | 0.00% |
| 517 | 111 | 1 | 0 | 0.00% |
| 4151 | 366 | 4 | 589 | 160.93% |
| 2907 | 366 | 2 | 2 | 0.55% |
| 2007 | 166 | 2 | 110 | 66.27% |
| 719 | 166 | 2 | 32 | 19.28% |
| 11492 | 111 | 4 | 194 | 174.77% |
| 7657 | 111 | 2 | 18 | 16.22% |

### 4.2.1 Cross-producting prefixes

Our scheme could reach $O(N^2)$ if there are duplicated prefixes in filter database (Figure 3.5). Looking at our scheme and the result of processing BGP routing table, our hypothesis is an AS whose duplicated prefixes percentage is high has high probability to result in high number of filters in structure compared to the number of filters in filter database.

For this simulation, We use filter databases created by cross-producting prefixes of two ASes: one that has duplicated prefixes, and one with no duplicated prefixes. We simulate these filter databases to confirm our hypothesis. For ASes without duplicated prefixes, we select five ASes whose number of prefixes rank on the top. For ASes with duplicated prefixes, we select three sets of ASes whose number of prefixes are equal. These ASes are displayed in Table 4.1.

### 4.2.2 Random prefixes

For filter databases consisted of random prefixes, we rank the ASes based on the four values above. Tables 4.2 to 4.5 show the top 5 ASes of each category. From these tables we have 16 distinct ASes, because several ASes appear twice.

Table 4.2: AS ranked by number of prefixes.

| AS num | Prefixes | Level | Dup. pref. | % Dup. pref. |
|---|---|---|---|---|
| 701 | 2202 | 3 | 426 | 19.35% |
| 1221 | 1422 | 3 | 176 | 12.38% |
| 7018 | 1091 | 2 | 156 | 14.30% |
| 702 | 1053 | 3 | 170 | 16.14% |
| 1 | 844 | 3 | 175 | 20.73% |

Table 4.3: AS ranked by maximum prefix level.

| AS num | Prefixes | Level | Dup. pref. | % Dup. pref. |
|---|---|---|---|---|
| 4787 | 47 | 6 | 146 | 310.64% |
| 9796 | 38 | 6 | 83 | 218.42% |
| 4323 | 584 | 5 | 549 | 94.01% |
| 6172 | 264 | 5 | 250 | 94.70% |
| 7843 | 208 | 5 | 358 | 172.12% |

Table 4.4: AS ranked by duplicated prefixes.

| AS num | Prefixes | Level | Dup. pref. | % Dup. pref. |
|---|---|---|---|---|
| 8010 | 720 | 2 | 698 | 96.94% |
| 4151 | 366 | 4 | 589 | 160.93% |
| 4323 | 584 | 5 | 549 | 94.01% |
| 3967 | 672 | 4 | 444 | 66.07% |
| 701 | 2202 | 3 | 426 | 19.35% |

Table 4.5: AS ranked by percentage of duplicated prefixes.

| AS num | Prefixes | Level | Dup. pref. | % Dup. pref. |
|---|---|---|---|---|
| 4787 | 47 | 6 | 146 | 310.64% |
| 9796 | 38 | 6 | 83 | 218.42% |
| 12150 | 28 | 4 | 56 | 200.00% |
| 21529 | 39 | 3 | 75 | 192.31% |
| 7908 | 78 | 4 | 147 | 188.46% |

We create two types of random filter databases for our simulations:

1. database with only non-wildcard filters
2. database with wildcard and non-wildcard filters

To create a non-wildcard filter database for this simulation, we select two ASes out of the 16 distinct ASes, namely *AS*-A and *AS*-B, create random prefixes from the prefixes of each AS, and we join two prefixes, one from *AS*-A and one from *AS*-B to form a two-dimensional filter.

A random prefix of an AS is formed as follows:

1. select $Prefix$ randomly from prefixes of AS
2. select $Subplen$ randomly between 0 and 32−prefix length of $Prefix$
3. create $SubPrefix$ as a random binary string with length of $Subplen$

4. concatenate $Prefix$ and $SubPrefix$ to create the result.

Simulating the non-wildcard filter databases, we make the combinations of all distinct ASes, thus we have 120 combinations. For each combination we create filter databases consisting of 2000, 4000, 10000, 20000, 40000, and 80000 filters, where for each size we create 5 filter databases.

For the case of filter databases with wildcard filters, we want to know the memory requirement of our scheme without the solution that is explained in Section 3.8. We choose 6 of above filter databases, formed by the pair of AS 701, 4787, 8010, and 9796 that consists of 20000 filters. We create wildcard filters sized 50, 100, 200, 500, 1000, and 2000 filters, containing random prefixes based on the prefixes of each AS. We add a wildcard filter database to the non-wildcard filter database formed from the same AS, thus we have 72 filter databases. For example, we add a wildcard filter created from AS 701 to non-wildcard filters created from AS 701 and 8010 pair.

We compile and run our implementation for each filter database on a Pentium III 1GHz machine running FreeBSD 4.3-RELEASE. This implementation is compiled using `gcc` without any compile time optimizations.

We record the memory requirement of each filter database and the time to build the data structure for non-wildcard filters. The build time is measured as *user time* in seconds obtained from `getrusage()` system call. Memory requirement is measured as the number of filters stored in all filter search planes. Results of these simulations are shown in the next sections. For filters with non-wildcard filters we average the data obtained from 5 filters whose AS pair and sizes are same before we present the results.

We also run the basic 2D packet classification scheme that is explained in Section 3.1 using several filter databases for comparison with our scheme.

## 4.3 Cross-product Filter Database Result

We display the result of our scheme for cross-product filter databases. Table 4.6 shows the number of filters stored in our scheme and Table 4.7 shows the numbers relative to filter database size.

Table 4.6: Filters in structure of cross-product filters.

| AS | 680 | 786 | 1913 | 4713 | 517 |
|---|---|---|---|---|---|
| 4151 | 93708 | 72097 | 45474 | 48693 | 46378 |
| 2907 | 84280 | 67024 | 45384 | 42916 | 40714 |
| 2007 | 41325 | 31639 | 20584 | 21225 | 20541 |
| 719 | 39809 | 31295 | 20599 | 20721 | 19615 |
| 11492 | 26944 | 20888 | 13764 | 13869 | 13321 |
| 7657 | 25792 | 20417 | 13764 | 13139 | 12501 |

Table 4.7: Percentage of filters in structure of cross-product filters.

| AS | 680 | 786 | 1913 | 4713 | 517 |
|---|---|---|---|---|---|
| 4151 | 111.319% | 107.643% | 100.198% | 113.710% | 114.158% |
| 2907 | 100.119% | 100.069% | 100.000% | 100.220% | 100.217% |
| 2007 | 108.237% | 104.151% | 100.000% | 109.283% | 111.478% |
| 719 | 104.267% | 103.019% | 100.073% | 106.688% | 106.453% |
| 11492 | 105.539% | 102.831% | 100.000% | 106.791% | 108.116% |
| 7657 | 101.026% | 100.512% | 100.000% | 101.170% | 101.461% |

## 4.4 Random Non-wildcard Filter Database Result

### 4.4.1 Build time

Figure 4.8 shows the time required to build data structure for the filter database. $x$ and $y$ axes are the number of filters in database (in thousands) and time to build the data structure (in seconds).

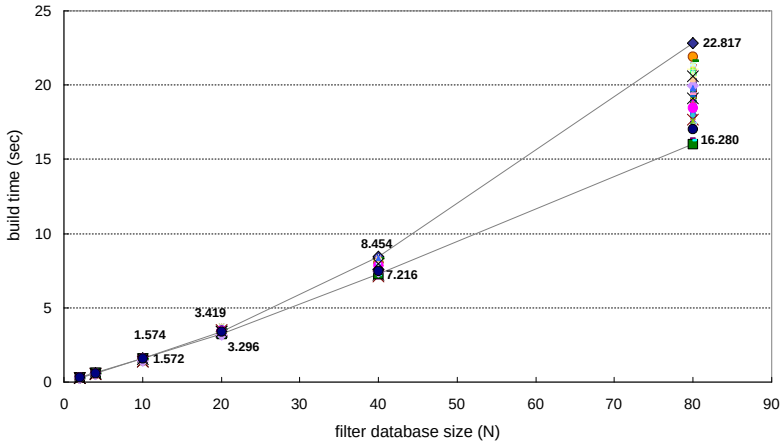



Figure 4.8: Time to build the data structure for all filter database.

### 4.4.2 Memory requirement

This sub section shows the memory requirement results for our simulations. The memory requirement is shown as the average number of filters stored in all FSPs of 5 random filter databases with same AS pairs and size. Figure 4.9 shows the combined result for all AS pairs and sizes. The $x$ axes is the number of filters in filter database and $y$ axes is the number of filters in the data structure of our scheme. Both $x$ and $y$ axes are shown in thousands scale.

To get more insight on the memory requirement, this sub section shows several figures of the number of filters in structure, which is shown as the relative percentage of the number

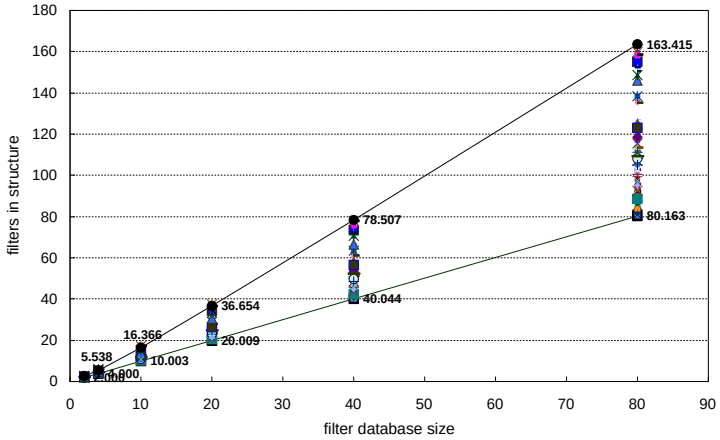



Figure 4.9: Filters in structure for all combinations.

of filters in the database. We show the result of filter databases created by pairing one of these ASes with the others: AS 701, 4787, 8010, and 9796. These AS rank number one in each category. We also display the result of AS 9796 because AS 4787 ranks number one twice and AS 9796 ranks second in both categories.

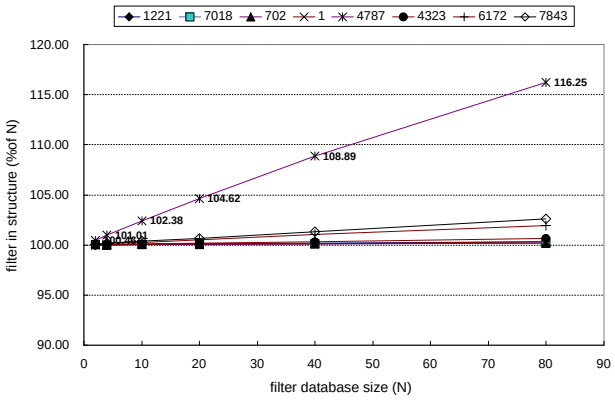



Figure 4.10: Filters of AS 701 pairing with other top 5 of prefix and level ASes.

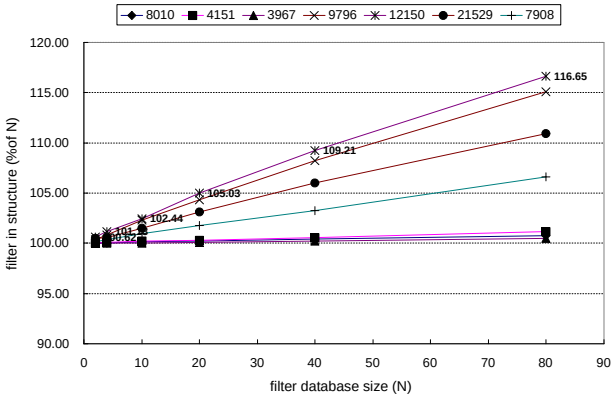



Figure 4.11: Filters of AS 701 pairing with other top 5 of duplicated prefix and the percentage ASes.

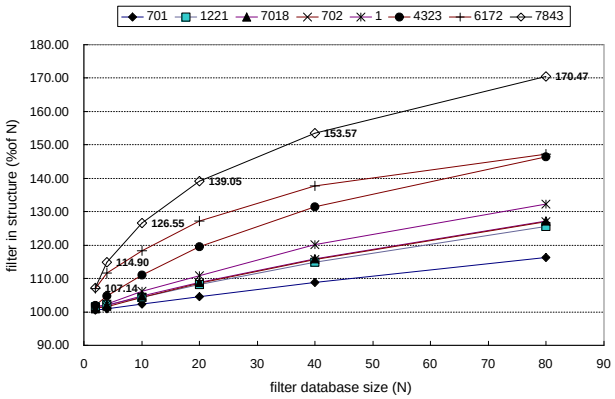



Figure 4.12: Filters of AS 4787 pairing with other top 5 of prefix and level ASes.

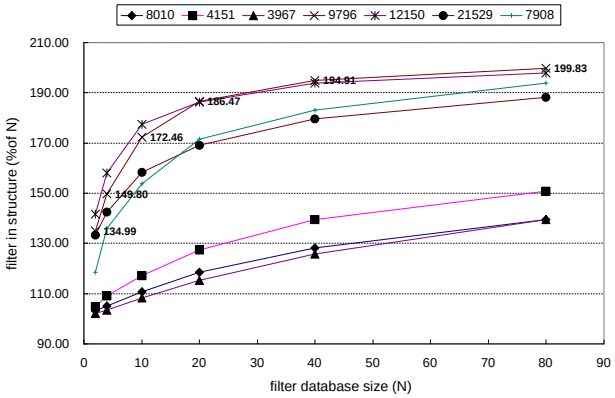



Figure 4.13: Filters of AS 4787 pairing with other top 5 of duplicated prefix and the percentage ASes.

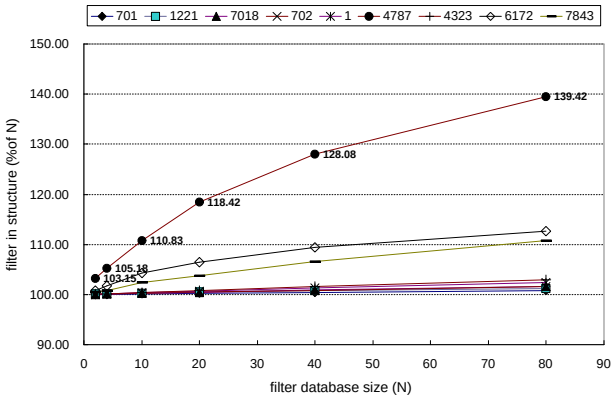



Figure 4.14: Filters of AS 8010 pairing with other top 5 of prefix and level ASes.

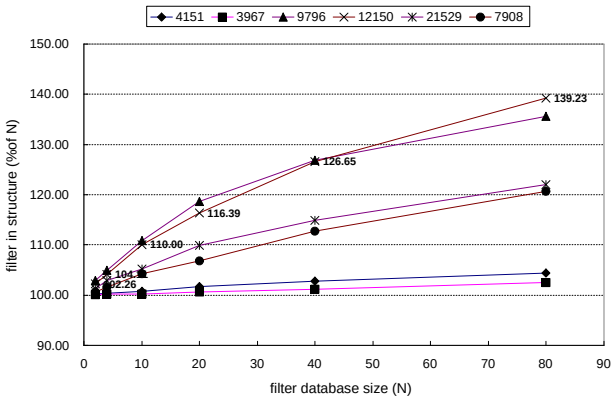



Figure 4.15: Filters of AS 8010 pairing with other top 5 of duplicated prefix and the percentage ASes.

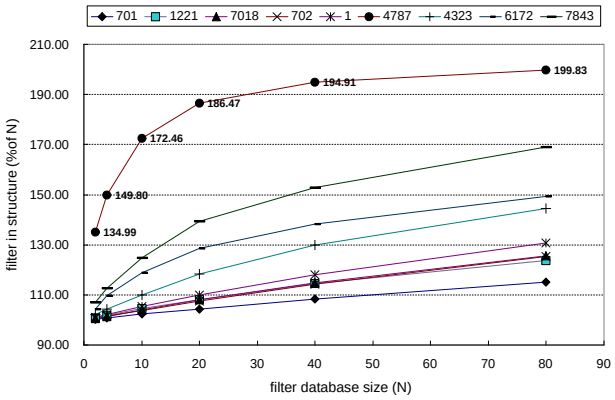



Figure 4.16: Filters of AS 9796 pairing with other top 5 of prefix and level ASes.

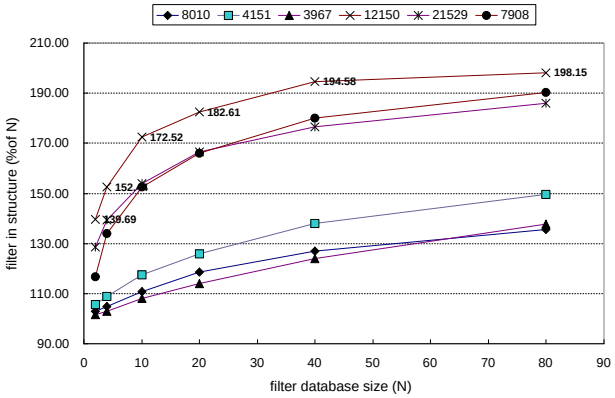



Figure 4.17: Filters of AS 9796 pairing with other top 5 of duplicated prefix and the percentage ASes.

## 4.5 Random Wildcard Filter Database Result

Figures 4.18 to 4.21 display the effect of adding wildcard filters to non-wildcard filter database. Each figure shows the result when we add wildcard filters created from an AS to a filter database sized 20000 filters. $x$ axes is the number of wildcard filters and $y$ axes is the number of filters in the structure relative to filter database size.

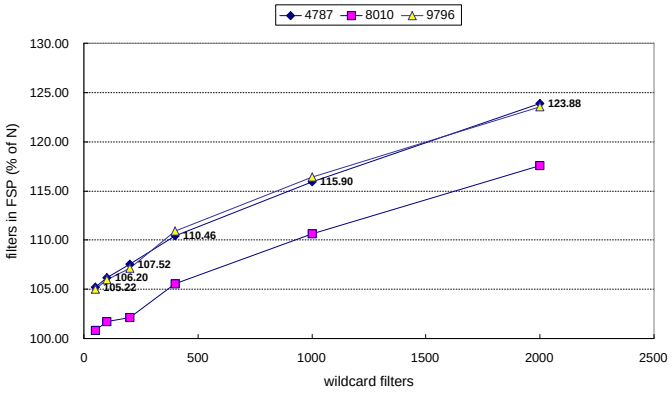



Figure 4.18: Adding wildcard filters created from AS 701.

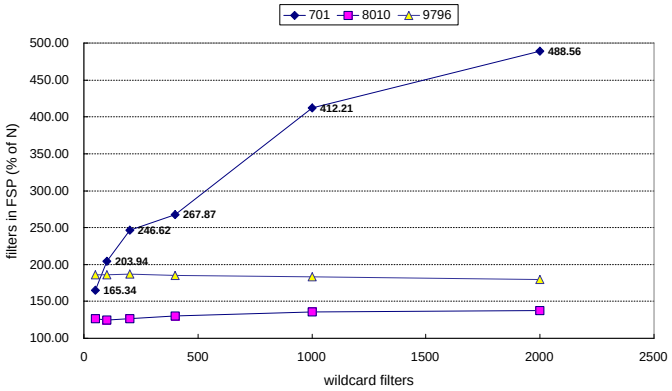



Figure 4.19: Adding wildcard filters created from AS 4787.

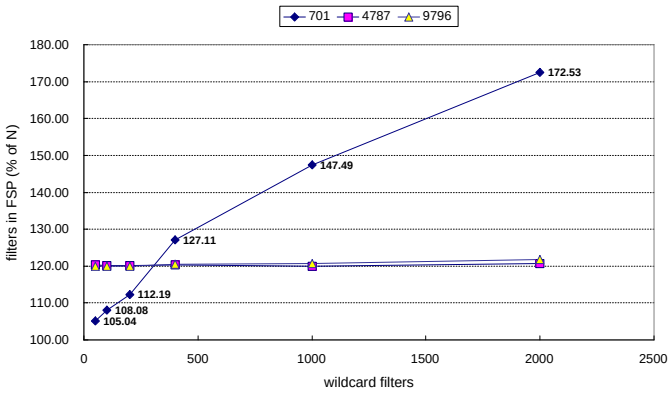



Figure 4.20: Adding wildcard filters created from AS 8010.

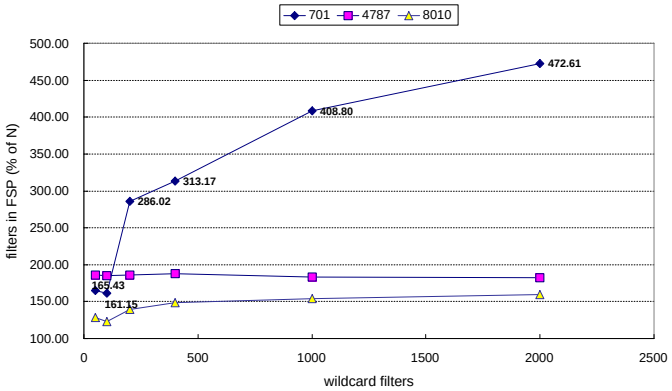



Figure 4.21: Adding wildcard filters created from AS 9796.

## 4.6 Memory Requirement of the Scheme in Section 3.1

We show in Figure 4.22 the result of simulations using the scheme in Section 3.1 for three filter databases, formed by pairing prefixes from AS 701 with the ones from AS 4787, 8010, and 9796. We do not perform many simulations using this scheme since the purpose is only as a comparison with our scheme.

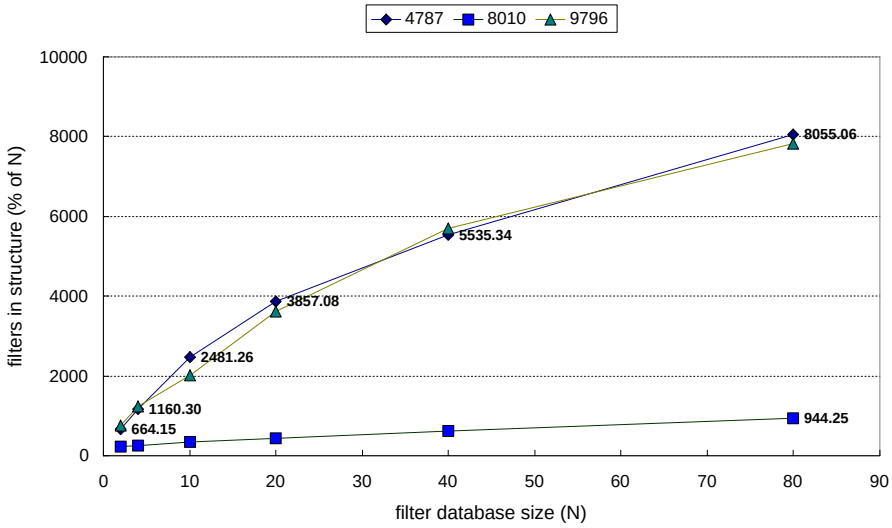



Figure 4.22: Filters of AS701 using the scheme in Section 3.1.

# Chapter 5

# Analysis and Evaluation

This chapter analyzes and evaluates our 2D packet classification scheme based on schemes' design and the simulation results. First we analyze the effect of duplicated prefixes to memory requirement, then we look into memory requirement of randomly generated filter database. We also analyze the time to build our data structure. We close this chapter by giving general evaluation of our two-dimensional packet classification scheme.

## 5.1 Effect of Duplicated Prefixes

Our hypothesis regarding this scheme is higher percentage of duplicated prefixes of filters in database can cause higher number of filters in the structure. Numbers in Table 4.7 seem to confirm this hypothesis, in general. We can see that filter databases created by ASes whose number of prefixes are the same but higher percentage of duplicated prefixes have higher percentage of filters in structure, except for the ones paired with AS 1913. When our filters with duplicated prefixes are paired with AS 1913, there is no consistent pattern that shows the effect of duplicated prefixes. AS 4151 has higher numbers than AS 2907, AS 2007 has lower numbers than AS 719, and AS 11492 and AS 7657 has the same numbers.

For our cross-product filter database case, a filter could be stored in more than one FSP only if the next conditions hold. Let's consider that we have a filter database created from AS $A$ and $B$. AS $A$ has no duplicated prefixes, while $B$ has some, and there is a prefix $PB1$ covering $PB2$ in $B$ and a prefix $PA1$ in $A$. $PB1$ could be stored in more than one FSP only if the prefix length of $PB1$ is shorter than that of $PA1$ and the prefix length of $PB2$ is longer than that of $PA1$. Figure 5.1 pictures this case. $F11$, formed by $PA1$ and $PB1$, is stored in two FSPs, $FSP(F11)$ and $FSP(F12)$.

A probe into prefixes of AS 1913 shows that all but five prefixes have prefix length of 24, and all those five prefixes have the length of 16. Looking into all ASes paired with AS 1913, we found that:

1. there is no prefix having length larger than 24,
2. only AS 4151 and 719 have prefixes whose length is less than 16 covering other prefixes.

These observations explain why we found low number of filters in structure for the cross products of AS 1913 with other ASes in our simulation. These also explain why AS 719

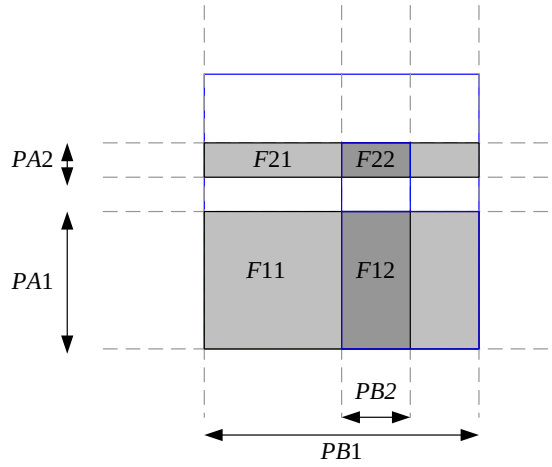



Figure 5.1: $F11$ is stored in $FSP(F11)$ and $FSP(F12)$.

has higher number of filters than AS 2007 even though AS 2007 has higher percentage of duplicated prefixes.

Analysis on this section shows that our hypothesis doesn't always hold. The reason for this is if we have two filters $F1$ and $F2$ where $F1$ covers $F2$ in one dimension, then whether $F1$ has to be stored in $FSP(F2)$ depends on the value of the other dimension of both filters (see Figure 3.5). However, this hypothesis can be used as a baseline to qualitatively predict the number of filters in structure of a filter database.

## 5.2 Memory Requirement

### 5.2.1 Non-wildcard filter database

Our results for non-wildcard filter databases show that, in general:

1. filter databases that we used in our simulations require at most about twice of the number of filters in the database (see Figure 4.9).

2. filter databases formed by ASes whose number of prefixes is small have higher percentage of filters in structure.

3. while the percentage of filters in structure increases as the number of filters in database increase, the trend shows that the increase in percentage is getting smaller.

Looking at Figures 4.10 to 4.17 and sorting them by the number of prefixes, we have the descending order of AS 701, 8010, 4787, and 9796. The series in each figure whose values are displayed are the ones that have the highest filters in structure when filter database size is 80-thousand filters. These series are shown in Figure 5.2. From this figure we can see that the order of these series from the lowest percentage to the highest one follows the descending order of ASes' number of prefixes.

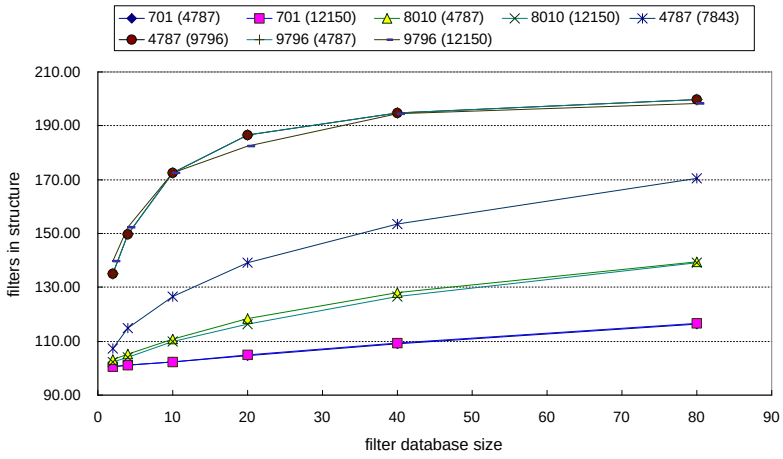



Figure 5.2: Top series of top 4 ASes.

The main reason for this is because at the same number of filters in our simulation, an AS whose number of prefixes is smaller generates more filters per ASes' prefix than the one with more prefixes. If we extract the field of filters generated from prefixes of a certain AS, we can see that more filters per prefix increases the probability of duplicated prefixes. Table 5.1 shows the distinct and duplicated prefixes generated from these four ASes. From these tables we can see that duplicated prefixes increase as the filter size increases, and ASes whose number of prefixes is small has higher probability to get more duplicated prefixes (in percentage) at the same filter database size.

Higher percentage of duplicated prefixes in our simulation means that the probability of having filters stored more than once increases. This is what we see in our memory requirement results. In our simulation, we generate prefixes of both dimensions of our filter databases randomly, thus it is difficult to predict how much filters have to be stored in more than one FSP.

Another trend that we see from Table 5.1 is the increase rate of distinct prefixes of an AS diminishes as the size of filter database increases. This trend exists because the more distinct prefixes created by random generator, the probability that the newly created prefixes will have the same value as the existing ones increases, therefore reducing the increase rate of distinct prefixes. This trend is also shown in our simulation result.

The above analysis shows that:

1. the increase of duplicated prefixes in the filter database contributes to the percentage increase of filters in structure

2. the diminishing increase rate of filters in structure as filter size increases is contributed by the increase rate of distinct prefixes, which is created randomly, is slowing.

### 5.2.2 Adding wildcard filters

Looking at the effect of wildcard filters if we run our scheme without the strategy of Section 3.1, we can see that adding wildcard filters created from AS 701 adds the percentage of

Table 5.1: Distinct and duplicated prefixes of ASes in filter databases.

| | AS 701 | | | AS 8010 | | |
|---|---|---|---|---|---|---|
| db size | prefixes | dupl. | pct. dup. | prefixes | dupl. | pct. dup. |
| 2k | 993 | 84 | 8.46% | 988 | 528 | 53.44% |
| 4k | 1971 | 339 | 17.20% | 1915 | 1430 | 74.67% |
| 10k | 4825 | 1805 | 37.41% | 4515 | 8994 | 199.20% |
| 20k | 9396 | 7661 | 81.53% | 8349 | 26887 | 322.04% |
| 40k | 17950 | 24356 | 135.69% | 14911 | 70876 | 475.33% |
| 80k | 33195 | 74070 | 223.14% | 25343 | 160992 | 635.25% |

| | AS 4787 | | | AS 9796 | | |
|---|---|---|---|---|---|---|
| db size | prefixes | dupl. | pct. dup. | prefixes | dupl. | pct. dup. |
| 2k | 777 | 5531 | 711.84% | 791 | 4792 | 605.82% |
| 4k | 1358 | 10280 | 757.00% | 1432 | 9980 | 696.93% |
| 10k | 2786 | 25969 | 932.12% | 2846 | 24472 | 859.87% |
| 20k | 4456 | 45497 | 1021.03% | 4752 | 44830 | 943.39% |
| 40k | 6965 | 75504 | 1084.05% | 7406 | 75010 | 1012.83% |
| 80k | 9854 | 111754 | 1134.10% | 10809 | 115216 | 1065.93% |

filters in structure of all filter databases of our simulation at roughly the same rate. On the other hand, the other three cases of wildcard filters additions don't show significant increase in percentage except for filter databases pairing with AS 701. Some filter databases even show a decrease in number of filters' percentage.

A pattern that we see here the ASes' number of distinct prefixes contributes to the difference percentage increase. This pattern is already discussed in the previous section, i.e. there are more filters per prefixes of an AS with lower number of distinct prefixes at a certain filter database size.

Another pattern is when wildcard filters are created from AS 4787, 8010, or 9796, filter databases created from AS 701 show a very high increase in number of filters' percentage. The other filter databases don't display this result. The main reason for this is AS 701 has higher number of top-level prefixes both in absolute and relative figures. A top-level prefix of a routing table is a prefix that is not covered by another prefix. Table 5.2 shows the number of distinct and top level prefixes of an AS.

Table 5.2: Distinct and top level prefixes of AS

| AS num | Prefixes | Top level |
|---|---|---|
| 701 | 2202 | 1813 |
| 4787 | 47 | 1 |
| 8010 | 720 | 22 |
| 9796 | 38 | 2 |

## 5.3 Build Time

Complexity analysis on the algorithms of our scheme shows that the time to build the data structure in memory is linear with the number of filters in filter database. Creating FSPs and their markers takes $O(NW)$, storing filters in FSPs requires $O(NW + WQ)$, and marking filters needs $O(NW)$ time. If no filter is stored more than once, then $Q = 0$, thus the build time is simply $O(NW)$. Because $W$, the bit-width of address, is a constant, then the build time is linear with $N$.

The fastest time to build data structure at each filter database size in Figure 4.8 is the case where build time is $O(NW)$ because the lowest figures in Figure 4.9 shows the number of filters in data structure is almost equal to the number of filters in the database. The lowest build times show that they are not linear to the number of filters. This is most likely due to cache memory misses. The more filters in database, the more memory and time are required. Using more memory means that less portion of the data structure fits in the processors' cache memory and it forces the processor to get the data from main memory more frequently. More time to build the data structure means that the operating system was probably doing more context-switching during the process. This also affects cache memory usage. This explains the deviation of build time from linear time, in case of no filter is stored more than once.

## 5.4 General Evaluation

In general our scheme is able to reduce memory usage compared to the basic scheme of Section 3.1. We can see from Figure 4.22 that the basic scheme requires very large memory because the probability of reaching $O(N^2)$ memory is high. Simulations of our scheme on the same filter databases show that our scheme saves much memory compared to the basic scheme even though both schemes have same worst-case memory requirement. This memory reduction comes with additional cost in time to search for the best matching filter, thus we can view our scheme as a time–space tradeoff of the basic scheme.

We evaluate the performance of this 2D packet classification scheme using simulated filter databases. While these filter databases are not the real ones, we believe that our method in generating them is sufficient to simulate real-life filter databases.

We do not simulate the search time of our scheme because complexity analysis of search time already shows that it is considerably fast and it is independent from the number of filters in database. Time to build data structure of our scheme is linear to the number of

filters, however we also need additional time in this process, which is linear to the number of duplicated filters. This linear build time is reached through several observations of the relationship between filters and FSPs.

A limitation of our 2D packet classification scheme is we cannot extend the scheme into more than two dimensions without reducing its memory saving capability. On a two-dimensional filter database, a filter marker in our scheme stores only one filter, which is the best one. This is not the case for higher dimensional filters. If we use this scheme for higher dimension filter database, whenever filters conflict in the source and destination fields, our scheme has to store all of them in order for the search algorithm to return the correct best matching filter. Therefore, the benefit of our scheme is reduced.

# Chapter 6

# Conclusion

## 6.1 Summary

In this thesis we described packet classification problem. Then we proposed a scheme for classifying Internet packet based on source and destination address fields to solve this problem. To evaluate our scheme, we performed simulation using randomly generated filter databases and we presented the results.

We explained packet processing in Internet routers and showed that an Internet router could process a packet several times using a function, which is packet classification, for different applications: QoS, firewall, etc. We showed that Internet routers need to have a good packet classification function so they can forward Internet packets as fast as their interface line speeds. This thesis then described the packet classification formally and summarized several related works in this fields.

The objective of a packet classification is to find the best matching filter (BMF) of a packet. This thesis explained a two-dimensional packet classification scheme, where the basic idea is to create many search planes and store filters in search planes. To search for the BMF of a packet, we use a two-step process:

1. search for the search plane containing BMF,
2. and then search for BMF in that search plane.

We create a search plane based on filters' definition. The assumption that we used in this research is fields of a filter can only take the form of prefixes. With this assumption we can create a search plane for a filter by using the shortest prefix length of the filter. We store a filter in a search plane if the filter crosses or covers the search plane. Using this strategy, a filter could be stored in more than one search plane, depending on the definition of both the filter and the search planes.

This scheme has the worst-case search time of $O(\log W)$. Through several observations, we are able achieve $O(NW + QW)$ time to build our data structure. $N$ is the number of filters in filter database; $W$ is the bitwidth of IP address; and $Q$ is the number of duplicated filters. The worst-case memory requirement of our scheme is $O(N^2W)$, however our scheme is designed to reduce the probability of reaching that worst-case. We also observed that we can prevent memory explosion caused by wildcard filters by separating them from non-wildcard filters. This can be achieved with an extra cost in search time.

This thesis evaluated the performance of our scheme using randomly generated filter databases. We modeled filter databases running on Autonomous System boundary routers. We ran our scheme using various random filter databases with different size. The simulation results showed that the memory usage tends to be closer to $O(NW)$ even though the worst-case is $O(N^2W)$. This is an important result of our scheme, which has never been explored before by others.

Table 6.1 shows our scheme among the other two-dimensional packet classification schemes. We can see that the worst-case lookup time and memory usage are comparable to cross-producting scheme. However, cross-producting tends to come close to the worst-case memory usage, and to reduce the memory usage, it uses a method to build data structure on-demand.

Table 6.1: Our scheme and other 2D packet classification schemes.

| Scheme | Lookup time | Memory usage |
|---|---|---|
| Tuple space search | $O(W^2)$ | $O(N)$ |
| Rectangle search | $O(W)$ | $O(NW)$ |
| Pruned tuple space | $O(W^2)$ | $O(N)$ |
| Grid of tries | $O(W)$ | $O(NW)$ |
| Cross-producting | $O(\log W)$ | $O(N^2)$ |
| Fast-2D | $O(\log^2 W)$ | $O(N\log^2 W)$ |
| **Our Scheme** | $O(\log W)$ | $O(N^2W)$ |

## 6.2 Future Work

A limitation of our scheme is we can use it for higher dimension packet classification, but with a reduction in memory saving capability. The main reason for this is for two-dimensional classification case, our scheme only needs to store the best filter in case of conflicting filters, but we cannot do this in higher-dimension case. This thesis does not address this problem. In the future, we will explore the performance of our scheme for higher-dimension packet classification.

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