A Computational Approach to Packet Classification

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ABSTRACT

Multi-field packet classification is a crucial component in modern software-defined data center networks. To achieve high throughput and low latency, state-of-the-art algorithms strive to fit the rule lookup data structures into on-die caches; however, they do not scale well with the number of rules.

We present a novel approach, NuevoMatch, which improves the memory scaling of existing methods. A new data structure, Range Query Recursive Model Index (RQ-RMI), is the key component that enables NuevoMatch to replace most of the accesses to main memory with model inference computations. We describe an efficient training algorithm which guarantees the correctness of the RQ-RMI-based classification. The use of RQ-RMI allows the packet rules to be compressed into model weights that fit into the hardware cache and takes advantage of the growing support for fast neural network processing in modern CPUs, such as wide vector processing engines, achieving a rate of tens of nanoseconds per lookup.

Our evaluation using 500K multi-field rules from the standard ClassBench benchmark shows a geometric compression factor of 4.9×, 8×, and 82×, and an average performance improvement of 2.7×, 4.4× and 2.6× in latency and 1.3×, 2.2×, and 1.2× in throughput compared to CutSplit, NeuroCuts, and TupleMerge, all state-of-the-art algorithms.

KEYWORDS

Packet Classification, Virtual Switches, Neural Networks

1 INTRODUCTION

Packet classification is a cornerstone of packet-switched networks. Network functions such as switches use a set of rules that determine which action they should take for each incoming packet. The rules originate in higher-level domains, such as routing, Quality of Service, or security policies. They match the packets’ metadata, e.g., the destination IP-address or and the used transport protocol. If multiple rules match, the rule with the highest priority is used.

Packet classification algorithms have been studied extensively. There are two main classes: those that rely on Ternary Content Addressable Memory (TCAM) hardware [12, 18, 21, 26, 32], and those that are implemented in software [2, 7, 19, 20, 29, 31, 36, 39]. In this work, we focus on software-only algorithms that can be deployed in virtual network functions such as forwarders or ACL firewalls, running on commodity X86 servers.

Software algorithms fall into two major categories: decision-tree based [7, 19, 20, 29, 36, 39] and hash-based [2, 31]. The former use decision trees for indexing and matching the rules, whereas the latter perform lookup via hash-tables by hashing the rule’s prefixes. Other methods for packet classification [6, 33] are less common as they either require too much memory or are too slow.

A key to achieving high classification performance in modern CPUs is to ensure that the classifier fits into the CPU on-die cache. When the classifier is too large, the lookup involves high-latency memory accesses, which stall the CPU as the data-dependent access pattern during the lookup impedes hardware prefetching. Unfortunately, as the number of rules grows, it becomes difficult to maintain the classifier in the cache. In particular, in decision-tree methods, rules are often replicated among multiple leaves of the decision tree, inflating its memory footprint and impeding scalability. Consequently, recent approaches, notably CutSplit [19] and NeuroCuts [20], seek to reduce rule replication to achieve better scaling. However, they still fail to scale to large rule-sets, which in modern data centers may reach hundreds of thousands of rules [5]. Hash-based techniques also suffer from poor scaling, as adding rules increases the number of hash-tables and their size.

Figure 1: NuevoMatch overview. The rules are divided into Independent Sets indexed by RQ-RMIs and the Remainder Set indexed by any classifier. One RQ-RMI predicts the storage index of the matching rule. The Selector chooses the highest-priority matching rule.

This work does not raise any ethical issues.
We propose a novel approach to packet classification, NuevoMatch, which compresses the rule-set index dramatically to fit it entirely into the upper levels of the CPU cache (L1/L2) even for large 500K rule-sets. We introduce a novel Range Query Recursive Model Index (RQ-RMI) model, and train it to learn the rules’ matching sets, turning rule matching into neural network inference. We show that RQ-RMI achieves out-of-L1-cache execution by reducing the memory footprint on average by 4.9×, 8×, and 82× compared to recent CutSplit [19], NeuroCuts [20], and TupleMerge [2] on the standard ClassBench [34] benchmarks, and up to 29× for real forwarding rule-sets.

To the best of our knowledge, NuevoMatch is the first to perform packet classification using trained neural network models. NeuroCuts performs offline decision tree parameter optimization during the tree construction phase using reinforcement learning. However, their rule matching uses traditional (optimized) decision trees. In contrast, NuevoMatch performs classification directly via RQ-RMIs, which are drastically more space-efficient than decision trees or hash-tables, improving scalability by an order of magnitude.

NuevoMatch transforms the packet classification task from memory- to compute-bound. This design is appealing because it is likely to scale well in the future, with rapid advances in hardware acceleration of neural network inference [10, 17, 27]. In contrast, the performance of both decision trees and hash-tables is inherently limited because of the poor scaling of DRAM access latency and CPU on-die cache sizes (e.g., 1.5× over five years for L1 in Intel’s CPUs).

NuevoMatch builds on the recent work on learned indexes [16], which applies a Recursive Model Index (RMI) model to indexing key-value pairs. The values are stored in an array, and the RMI is trained to learn the mapping function between the keys and the indexes of their values in the array. The model is used to predict the index given the key. The paper [16] applies RMI to databases, boosting performance by compressing the indexes to the size of CPU caches.

Unfortunately, RMI is not directly applicable for packet classification. First, a key (packet field) may match a rule range, whereas RMI learns only exact key-index pairs. This is a fundamental property of RMI: it guarantees correctness only for the keys used during training, but provides no such guarantees for non-existing keys ([16], Section 3.4), which makes it inapplicable for range matching. Second, the match is evaluated over multiple packet fields, requiring lookup in a multi-dimensional space. Unfortunately, multi-dimensional RMI [15] requires that the input be flattened into one dimension, which in the presence of wildcards results in an exponential blowup of the input domain, making it too large to learn in compact models. Finally, a key may match multiple rules, with the highest priority one used as output, whereas RMI retrieves only a single index for each key.

NuevoMatch successfully solves these challenges.

**RQ-RMI.** We design a novel RQ-RMI model to allow keys to be matched to ranges, with a training algorithm that guarantees range lookup correctness. The training strives to minimize the prediction error of the index, while maintaining a small model size. We show that the models can store indexes of 500K ClassBench rules in 35 KB (§5.2.1). We prove that our algorithm achieves strict error bounds, guaranteeing its correctness in lookup queries (§3.3).

**Multi-field packet classification.** To enable multi-field matching with overlapping ranges, the rule-set is split into independent sets with non-overlapping ranges, called iSets, each associated with a single field and indexed with its own RQ-RMI model. The iSet partitioning (§3.6) strives to cover the rule-set with as few iSets as possible, discarding those that are too small. The remainder set of the rules not covered by large iSets is indexed via state-of-the-art classification techniques. In practice, the rules in the remainder constitute a small fraction in representative rule-sets, allowing the index to fit into fast cache together with the RQ-RMIs.

Figure 1 summarizes the complete classification flow. All RQ-RMI models and the remainder are queried in parallel. The results are used as hints for the secondary search that selects one matching rule per iSet. A validation stage filters out the candidates with a positive match across all fields, and a selector chooses the highest priority rule. This process is guaranteed to produce a correct output.

Conceptually, NuevoMatch can be seen as an accelerator for existing packet classification techniques and thus complements them. In particular, the RQ-RMI model is best used for indexing rules with high value diversity that can be partitioned into fewer iSets. We show that the iSet construction algorithm is effective for selecting the rules that can be indexed via RQ-RMI, leaving the rest in the remainder (§5.3.1). The performance benefits of NuevoMatch become evident when it indexes more than 25% of the rules. Since the remainder is only a fraction of the original rule-set, it can be indexed efficiently with smaller decision-trees/hash-tables or will fit smaller TCAMs.

Our experiments showed that NuevoMatch outperforms the state-of-the-art algorithms, reaching up to a geometric improvement of 2.7×, 4.4× and 2.6× in latency and 1.3×, 2.2×, and 1.2× in throughput vs. CutSplit, NeuroCuts, and TupleMerge, respectively, for the sets of 500K ClassBench-generated 5-field rules. We also measure 3.5× higher throughput and 7.5× lower latency vs. TupleMerge for the real-world Stanford backbone forwarding rule-set.

NuevoMatch supports rule updates by promptly removing the updated rules from the RQ-RMI and adding them to the remainder set indexed by an algorithm that supports fast
updates, e.g., TupleMerge. This approach requires periodic retraining to maintain small remainder set, hence it does not yet support more than a few thousands of updates. We analyze the current support in (§3.9), but defer the algorithmic solution to directly update RQ-RMI for future work.

In summary, our contributions are as follows:
- We present an RQ-RMI model and a novel training technique for learning packet classification rules with guaranteed matching correctness.
- We demonstrate the application of RQ-RMI to multi-field packet classification.
- NuevoMatch outperforms existing techniques in terms of memory footprint, latency, and throughput on challenging rule-sets with up to 500K rules, compressing them to fit into small caches of modern processors.

2 BACKGROUND

This section describes the packet classification problem and surveys existing solutions.

2.1 Classification algorithms

Packet classification is the process of locating a single rule that is satisfied by an input packet among a set of rules. A rule contains several fields in the packet’s metadata. Wildcards define ranges, i.e., they may match multiple values. Ranges may overlap with each other, i.e., a packet may match several rules, but only the one having the highest priority is selected. Figure 2 illustrates a classifier with two fields and five overlapping matching rules. An incoming packet matches two rules ($R^1, R^5$), but $R^4$ is used as it has a higher priority.

Packet classification performance becomes difficult to scale as the number of rules and the number of matching fields grow. Therefore, it has received renewed interest with increased complexity of software-defined data center networks, featuring hundreds of thousands of rules per virtual network function [4] and tens of matching fields (up to 41 in OpenFlow 1.4 [25]).

Decision Tree Algorithms. The rules are viewed as hypercubes and packets as points in a multi-dimensional space. The axes of the rule space represent different fields and hold non-negative integers. A recursive partitioning technique divides the rule space into subsets with at most $bith$ rules. Thus, to match a rule, a tree traversal finds the smallest subset for a given packet, while a secondary search scans over the subset’s rules to select the best match.

Unfortunately, a rule replication problem may hinder performance in larger rule-sets by dramatically increasing the tree’s memory footprint when a rule spans several subspaces. Early works, such as HiCuts [7] and HyperCuts [29] both suffer from this issue. More recent EffiCuts [36] and

| IPv4 Address | Port | Priority | Action |
|--------------|------|----------|--------|
| 10.10.*.*.   | 10-18| 1 (highest) | $a_{41}$ |
| 10.10.1.*.*  | 10-25| 2        | $a_{41}$ |
| 10.10.2.*.*  | 5-8  | 3        | $a_{41}$ |
| 10.10.3.*.*  | 3-15 | 4        | $a_{41}$ |
| 10.10.3.100  | 5-20 | 4 (lowest) | $a_{41}$ |

Incoming packet 10.10.3.100.19 Action to take $a_{41}$

Figure 2: Packet classification with two fields: IP address and port.

CutSplit [19], suggest that the rule set should be split into groups of rules that share similar properties and generate a separate decision-tree for each. NeuroCuts [20], the most recent work in this domain, uses reinforcement learning for optimizing decision tree parameters to reduce its memory footprint, or the number of memory accesses during traversal, by efficiently exploring a large tree configuration space.

Hash-Based Algorithms. Tuple Space Search [31] and recent TupleMerge [2] partition the rule-set into several subsets according to the number of prefix bits in each field. As all rules of a particular subset have the same number of prefix bits, they can act as keys in a hash table. The classification is performed by extracting the prefix bits, in all fields, of an incoming packet, and checking all hash-tables for matching candidates. A secondary search eliminates false-positive results and selects the rule with the highest priority.

Hash-based techniques are effective in an online classification problem with frequent rule updates, whereas decision trees are not. On the other hand, decision trees have been traditionally considered faster in classification. Nevertheless, the recent TupleMerge hash-based algorithm closes the gap and achieves comparable classification throughput while supporting high performance updates.

2.2 Poor performance with large rule-sets

The packet classification performance of all the existing techniques does not scale well with the number of rules. This happens because their indexing structures spill out of the fast L1/L2 CPU caches into L3 or DRAM. Indeed, as we show in our experiments (§5), TupleMerge and NeuroCuts exceed the 1MB L2 cache with 100K rules and CutSplit with 500K rules. However, keeping the entire indexing structure in a fast cache is critical for performance. The inherent lack of access locality in hash and tree data structures, combined with the data-dependent nature of the accesses, make hardware prefetchers ineffective for hiding memory access latency. Thus, the performance of all lookups drops dramatically.

The performance drop is significant even when the data structures fit in L3 cache. This cache is shared among all the
We first explain the RMI model for learned indexes which we use as the basis, explain its limitations, and then show the submodels in each stage are trained on a progressively smaller subset of the input keys, in order to refine the index prediction toward the submodels in the leaves. Thus, each key-index pair is learned by one submodel at each stage, with the leaf submodel producing the index prediction.

RMI is a generic structure, thus a variety of machine learning models can be used as submodels, including linear regression or neural networks. The type of the submodels, the number of stages and the width of each stage are configured prior to training.

**Training.** Training is performed stage by stage.

*First stage.* The submodel in stage $m_{0,0}$ is trained on the whole data set. Then, the input key-index pairs are split into $W_i$ disjoint subsets. The input partitioning is performed as follows. For each input key-index pair $\{key : idx\}$ we compute the model prediction $\hat{y} = m_{0,0}(key)$, satisfying $\hat{y} \in [0, 1]$. The output $\hat{y}$ is used to obtain $j = \lfloor \hat{y} \cdot W_i \rfloor$ which is the index of the submodel in stage 1, $m_{1,j}$, to be used for learning $\{key : idx\}$. We call the subset of the input to be learned by model $m_{1,j}$ as model input responsibility domain $R_{i,j}$, or responsibility for short. $R_{0,0}$ is the whole input.

*Internal stages.* The submodels in stage $i$, $m_{i,j}$, are trained on the keys in $R_{i,j}$ $j < W_i$. After training, the responsibilities of the submodels in stage $i+1$ are computed, and the process continues until the last stage.

*Last stage.* The submodels of the last stage must predict the actual index of the matching value in the value array. However, a submodel may have a prediction error. Therefore, RMI uses the model prediction as a hint. The matching value is found by searching in the value array in the vicinity of the predicted index, as defined by the maximum error bound $\epsilon$ of the model. Note that $\epsilon$ should be valid for all input key-index pairs. To compute $\epsilon$, RMI exhaustively computes the submodel prediction for each input key in its responsibility. Submodels with high error bound are retrained.

**Inference.** Given a key, we iteratively evaluate each submodel stage after stage, from $m_{0,0}$. We use the prediction in stage $i−1$ to select a submodel in stage $i$, until we reach the last stage. The last selected submodel predicts the index in the value array. This index $\tilde{i}$ determines the range for the secondary search in the value array that spans $[\tilde{i} - \epsilon, \tilde{i} + \epsilon]$.

### 3.2 RMI limitations

Direct application of RMI to indexing packet classification rules is not possible for the following reasons:

**No support for range matching**

RMI allows only an exact match for a given key, whereas packet classification requires to retrieve rules with matching ranges as defined by

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Figure 3: RMI model structure and inference [16].

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The RMI paper also uses the term range index while applying RMI to range index data structures (i.e., B-trees) that can quickly retrieve all stored keys in a requested numerical range. Our work is fundamentally different: given a key it retrieves the indexes of matching ranges.
wildcards. This problem is fundamental: RMI exhaustively scans all the keys in all the ranges to calculate the submodel responsibility and the maximum model prediction error (see the underlined parts of the training algorithm). In other words, all the values in the range must be materialized into key-index pairs for RMI to learn them, since RMI does not guarantee correct lookup for keys not used in training [16]. The original paper sketches a few possible solutions to this problem. However, they either rely on model monotonicity (while we do not) or require smarter enumeration techniques (which are still expensive).

**Ineffective multi-dimensional indexing.** RMI is ineffective for multi-dimensional indexes because the proposed solution [15] leads to generating an exponential number of rules in the presence of wildcards. For example, a single rule with wildcards in destination IP (0.0.0. *), port (10-100), and protocol (TCP/UDP) results in 46,592 distinct key-index pairs. Since the input domain becomes too large, it can be learned only by a large model that exceeds the CPU cache.

We outline the solutions to these challenges below.

### 3.3 One-dimensional RQ-RMI

We first seek to find a way to perform range matching over a set of non-overlapping ranges in one dimension.

**3.3.1 Intuition.** There are two basic ideas:

**Sampling.** Each submodel \( m_{i,j} \) is trained by generating a uniform sample of key-index pairs from input ranges in its responsibility. The samples are generated on-the-fly for each submodel (§3.5.3).

**Analytical error bound estimation for ranges.** We eliminate the RMI’s exhaustive enumeration by making the following observation: if a submodel is a piece-wise linear function, the worst-case error bound \( \epsilon \) can be computed analytically, thereby enabling efficient learning of ranges.

The intuition behind this observation is illustrated in Figure 4. It shows the graph of some piece-wise linear function which represents a submodel \( M \) whose outputs are quantized into integers in \([0,4]\), i.e., \( M \) predicts the index in an array of size 4. We call the inputs for which this function changes its quantized output transition inputs \( t_i \in T \). In turn, transition inputs determine the region of inputs with the same quantized output. Therefore, given an input range in the model’s responsibility, to compute the model’s maximum prediction error for any key in that range, it suffices to evaluate the prediction error in the transition inputs that fall in the range. We describe the training algorithm that relies on these observations in Section 3.4.

We now provide a more formal description, but leave most of the proofs in the Appendix.

### 3.4 Using a neural network as a submodel

We choose to use a 3-layer fully-connected neural network (NN) with a single hidden layer and ReLU activation \( A \). Such NNs have been suggested in the original RMI paper [16], however they did not leverage their properties for accelerating error bound computations.

**Definition 3.1 (RQ-RMI submodel).** Denote the output of a 3-layer fully-connected neural network as:

\[
N_{i,j}(x) = A(x \cdot w_1 + b_1) \times w_2 + b_2
\]

where \( x \) is a scalar input, \( w_1, b_1 \) are the weight and bias row-vectors for layer 1 (hidden layer), and \( w_2, b_2 \) are the weight column-vector and bias scalar for layer 2. Note that \( N_{i,j}(x) \) is a scalar. The ReLU function \( A \) applies a function \( a \) on each element of an input vector:

\[
a(x) = \begin{cases} 
  x & x \geq 0 \\
  0 & x < 0.
\end{cases}
\]

The submodel output, denoted \( M_{i,j}(x) \), is defined as follows:

\[
M_{i,j}(x) = H(N_{i,j}(x))
\]

where \( H(x) \) is a function which guarantees that the output domain is trimmed to \([0,1]\).

**Corollary 3.2.** \( M_{i,j}(x) \) is a piece-wise linear function.

### 3.5 RQ-RMI training

We use Corollary 3.2 to compute the transition inputs and the responsibility of the submodels. We provide a simplified description, see Appendix for precise explanation.

**3.5.1 Computing transition inputs.** Given a trained submodel \( m \) we can analytically find all its linear regions, and respectively the inputs delimiting them, which we call trigger inputs \( g_i \). For all inputs in the region \([g_i, g_{i+1}]\), the model function, denoted as \( M(x) \) is linear by construction. On the other hand, the uniform output quantization defines a step-wise function \( Q = \lfloor M(x) \cdot W \rfloor / W \), where \( W \) is the size of the quantized output domain. Thus, for each input region \([g_i, g_{i+1}]\), the set of transition inputs \( t_i \in T \) are those where \( M(x) \) and \( Q \) intersect.
3.5.2 Computing the responsibilities of submodels in the following stage. Given a trained submodel \( m_{i,j} \) in an internal stage \( i \), we say that it maps a key \( k \) to a submodel \( m_{i+1,k} \), \( k < W_{i+1} \), if \( \{ M_{i,j}(key) \cdot W_{i+1} \} = k \). As discussed informally earlier, the responsibility \( R_{i+1,k} \) of \( m_{i+1,k} \) is defined as all the inputs which are mapped by submodels in stage \( i \) to \( m_{i+1,k} \). In other words, the trained submodels at stage \( i \) define the responsibility of untrained submodels at stage \( i + 1 \).

Knowing the responsibility of a submodel is crucial as it determines the subset of the inputs used to train the submodel. RMI exhaustively evaluates over all the inputs, which is inefficient. Instead, we compute \( R_{i+1,k} \) using the transition inputs of \( m_{i,j} \). In the following we assume for clarity that \( R_{i,j} \) is contiguous, and \( m_{i,j} \) is the only submodel at stage \( i \).

We compute \( R_{i+1,k} \) by observing that it is composed of all the inputs in the regions \( (t_1, t_1 + 1) \) which map to submodel \( m_{i+1,k} \), where \( t_1 \in T_{i,j} \) are transition inputs of \( m_{i,j} \). By construction, the inputs in the region between two adjacent transition points map to the same output. Then, it suffices to compute the output of \( m_{i,j} \) for its transition points, and choose the respective input ranges that are mapped to \( m_{i+1,k} \).

3.5.3 Training a submodel with ranges using sampling. Up to this point we used only key-index pairs as model inputs. Now we focus on training on input ranges. A range can be represented as all the keys that fall into the range, all associated with the same index of the respective rule. For example, 10.1.1.0-10.1.1.255 includes 256 keys. Our goal is to train a model such that given a key in the range, the model predicts the correct index. Enumerating all the keys in the ranges is ineffective. Instead, we use sampling as follows.

The training is performed in three steps repeated as needed: sample generation, submodel training, maximum error computation. If the maximum error is too large, the model is retrained.

Sample generation. We generate the training key-index pairs by uniformly sampling the submodel’s responsibility. We start with a low sampling frequency. A sample is included in the training set if there is an input rule range that matches the sampled key. Thus, the number of samples per input range is proportional to its relative size in the submodel’s responsibility. Note that some input ranges (or individual keys) might not be sampled at all. Nevertheless, they will be matched correctly as we explain further.

Neural network training. We train the submodel using the generated samples via standard stochastic gradient descent training with mean squared error loss function.

Maximum error computation. Given a trained submodel, we compute the prediction error bound for all inputs in its responsibility by evaluating the submodel on its transition inputs. The prediction error is computed also for the inputs that were not necessarily sampled, guaranteeing match correctness. If the error is too large, we increase the input sampling frequency, regenerate the key-index pairs, and retrain the submodel. Training continues until the target error bound is attained. If training does not converge, the target error bound is increased. Note that the error bound determines the search distance of the secondary search, hence larger bound causes lower system performance. We evaluate this tradeoff later (§3.5.4).

3.5.4 Training an RQ-RMI. The whole training process is similar to RMI’s and is performed stage by stage. For each stage, we train each submodel separately according to §3.5.3. We then compute the responsibilities of the submodels in the next stage, and train them, and so on, until the last stage.

3.6 Handling multi-dimensional queries with range overlaps

NuevoMatch supports overlapped ranges and matching over multiple dimensions, i.e., packet fields, by combining two simple ideas: partitioning the rule-set into disjoint independent sets (iSets), and performing multi-field validation of each rule. In the following, we use the terms dimension and field interchangeably.

Partitioning. Each iSet contains rules that do not overlap in one specific dimension. We refer to the coverage of an iSet as the fraction of the rules it holds out of those in the input. One iSet may cover all the rules if they do not overlap in at least one dimension, whereas the same dimension with many overlapping ranges may require multiple iSets. Figure 5 shows the iSets for the rules from Figure 2.

Each iSet is indexed by one RQ-RMI. Thus, to find the match to a query with multiple fields we query all RQ-RMIs (in parallel), each over the field on which it was trained. Then, the highest priority result is selected as the output.

Each iSet adds to the total memory consumption and computational requirements of NuevoMatch. Therefore, we introduce a heuristic that strives to find the smallest number of iSets that cover the largest part of the rule-set (§3.6.1).
Multi-field validation. Since an RQ-RMI builds an index of the rules over a single field, it might retrieve a rule which does not match against other fields. Hence, each rule returned by an RQ-RMI is validated across all fields. This enables NuevoMatch to avoid indexing all dimensions, yet obtain correct results.

3.6.1 iSet partitioning. We introduce a greedy heuristic that repetitively constructs the largest iSet from the input rules, producing a group of iSets. To find the largest iSet over one dimension, we use a classical interval scheduling maximization algorithm [13]. The algorithm sorts the ranges by their upper-bounds, and repetitively picks the range with the smallest upper-bound that does not overlap previously selected ranges.

We apply the algorithm to find the largest iSet in each field. Then we greedily choose the largest iSet among all the fields and remove its rules from the input set. We continue until exhausting the input. This heuristic is sub-optimal but quite efficient. We plan to improve it in future work.

Having larger number of fields in a rule-set might help improve coverage. For example, if the rules that overlap in one field do not overlap in another and vice versa, two iSets cover the whole rule-set, requiring more iSets for each field in isolation.

3.7 Remainder set and external classifiers

Real-world rule-sets may require many iSets for full coverage, with a single rule per iSet in the extreme cases. Using separate RQ-RMIs for such iSets will hinder performance. Therefore, we merge small iSets into a single remainder set. The rules in the remainder set are indexed using an external classifier. Each query is performed on both the RQ-RMI and the external classifier.

In essence, NuevoMatch serves as an accelerator for the external classifier. Indeed, if rule-sets are covered using a few large iSets, the external classifier needs to index a small remainder set that often fits into faster memory, so it can be very fast.

Two primary factors determine the end-to-end performance: (1) the number of iSets required for high coverage (depends on the rule-set), and; (2) the number of iSets for achieving high performance (set by an operator).

Our evaluation (§5.3.1) shows that most of the evaluated rule-sets can be covered with high coverage above 90% with only 2-3 iSets. This is enough to accelerate the external classifier, as is evident from the performance results. On the other hand, the choice of the number of iSets depends on the external classifier properties, in particular, its sensitivity to memory footprint. We analyze this tradeoff in §5.3.

Worst-case inputs. Some rule-sets cannot achieve good coverage with few iSets. For example, a rule-set with a single field whose ranges overlap requires too many iSets to be sufficiently covered.

To obtain a better intuition about the origins of worst-case inputs, we consider the notion of rule-set diversity for rule-sets with exact matches. Rule-set diversity in a field is the number of unique values in it across the rule-set, divided by the total number of rules. The rule-set diversity is an upper bound on the fraction of rules in the largest iSet of that field. In other words, low rule diversity implies that using the field for iSet partitioning would result in poor coverage.

We can also identify challenging rule-sets with ranges. We define rule-set centrality as the maximum number of rules that each pair of them overlap (they all share a point in a multi-dimensional space). The rule-set centrality is a lower bound on the number of iSets required for full coverage.

The diversity and centrality metrics can indicate the potential of NuevoMatch to accelerate the classification of a rule-set. On the positive side, our iSet partitioning algorithm is effective at segregating the rules that cannot be covered well from the rules that can, thereby accelerating the remainder classifier as much as possible for a given rule-set. We analyze this property in §5.3.3.

3.8 Putting it all together

We briefly summarize all the steps of NuevoMatch.

Training

(1) Partition the input into iSets and a remainder set
(2) Train one RQ-RMI on each iSet
(3) Construct external classifier for the remainder set

Lookup

(1) Query all the RQ-RMIs
(2) Query (in parallel) the external classifier
(3) Collect all the outputs, return the highest-priority rule

3.9 Rule Updates

We explain how NuevoMatch can support updates with a limited performance degradation.

Firstly, an external classifier used for the remainder must support updates. Among the evaluated external classifiers only TupleMerge is designed for fast updates.

Secondly, we distinguish four types of updates: (i) a change in the rule action; (ii) rule deletion (iii) rule matching set change; (iv) rule addition.

The first two types of updates are supported without performance degradation, and require a lookup followed by an update in the value array. However, if an update modifies a
Figure 6: Updates impact on Throughput over time. An upper bound (in green) is zero training every update.

rule’s matching set or adds a new rule, it might require modifications to the RQ-RMI model. We currently have no algorithmic way to update RQ-RMI without retraining; therefore, an updated rule is always added to the remainder set.

Unfortunately, this design leads to gradual performance degradation, as updates are likely to increase the remainder set. Accordingly, the model is retrained on the updated rule-set, either periodically or when a large performance degradation is detected. Updates occurring while retraining are accommodated in the following batch of updates.

Estimating sustained update rate. Let $r$ and $u$ be the total number of rules and the number of updates that move a rule to the remainder, respectively. $u$ can be smaller than the real rate of rule updates. We assume that the updates are independent and uniformly distributed among the $r$ rules. For each rule update, a rule is modified w.p. (with probability) $\frac{1}{r}$. Thus a rule is not modified in any of the updates w.p. $(1 - \frac{1}{r})^u \approx e^{-u/r}$. The expected number of unmodified rules is $r \cdot (1 - \frac{1}{r})^u \approx r \cdot e^{-u/r}$. Throughput behaves as a weighted average between that of NuevoMatch and the remainder implementation, based on the number of rules in each.

Figure 6 illustrates the throughput over time for different retraining rates given a certain update rate. If retraining is invoked every $\tau$ time units, the slower the training process, the worse the performance degradation.

With these update estimates, using the measured speedup as a function of the fraction of the remainder (§5.3.3), NuevoMatch can sustain up to 4k updates/s for 500K rule-sets, yielding about half the speedup of the update-free case, assuming a minute-long training. These results indicate the need for speeding up training, but we conjecture there might be a more efficient way to perform updates directly in RQ-RMI without complete re-training of all submodels. Accelerating updates is left for future work.

4 IMPLEMENTATION DETAILS

RQ-RMI structure. The number of stages and the width of each stage depend on the number of rules to index. We increase the width of the last stage from 16 for 10K rules to up to 512 for 500K. See Table 4 in the Appendix.

| Instruction set (width) | Serial(1) | SSE(4) | AVX(8) |
|-------------------------|-----------|--------|--------|
| Inference Time (ns)     | 126       | 62     | 49     |

Table 1: Submodel acceleration via vectorization. Methods are annotated with the number of floats per single instruction.

Submodel structure. Each submodel is a fully connected 3-layer neural net with 1 input, 1 output, and 8 neurons in the hidden layer with ReLU activation. This structure affords efficient vectorized implementation (see below).

Training. We use TensorFlow [1] to train each submodel on a CPU. Training a submodel requires a few seconds, but the whole RQ-RMI may take up to a few minutes (See §5.3.4). We believe, however, that a much faster training time could be achieved with more optimizations, i.e., replacing TensorFlow (known for its poor performance on small models). We leave it for future work.

Inference and secondary search. We implement RQ-RMI inference in C++. For each iSet we sort the rules by the value of the respective field to optimize the secondary search. To reduce the number of memory accesses, we pack multiple field values from different rules in the same cache line.

Handling long fields. Both iSet partitioning algorithms and RQ-RMI models map the inputs into single-precision floating-point numbers. This allows packing more scalars in vector operations, resulting in faster inference. While enough for 32-bit fields, doing so might cause poor performance for fields of 64-bits and 128-bits.

We compared two solutions: (1) splitting the fields into 32-bit parts and treating each as a distinct field, and (2) using a single-precision floating-point to express long fields. The two showed similar results for iSet partitioning with MAC addresses, while with IPv6, splitting into multiple fields worked better. Note that both the secondary search and the validation phases are not affected because the rules are stored with the original fields.

Vectorization. We accelerate the RQ-RMI model inference by using wide CPU vector instructions. Specifically, with 8 neurons in the hidden layer of each submodel, computing the prediction involves a handful of vector instructions. Validation is also vectorized.

Table 1 shows the effectiveness of vectorization. The use of wider units speeds up inference, highlighting the potential for scaling NuevoMatch in future CPUs.

Parallelization. NuevoMatch lends itself to parallel execution where iSets and the remainder classifier run in parallel on different CPU cores. The system receives the packets and enqueues each for execution into the worker threads.
threads are statically allocated to run RQ-RMI or the external classifier with a balanced load between the cores.

Note that since RQ-RMI are small to fit in L1, running them on a separate core enables out-of-L1-cache execution even if the remainder classifier is large. Such an efficient cache utilization could not have been achieved with other classifiers running on two cores.

5 EVALUATION

In the evaluation, we pursued the following goals.

1. End-to-end comparison of NuevoMatch with the state-of-the-art algorithms TupleMerge [2], CutSplit [19], and NeuroCuts [20];
2. Systematic analysis of the performance characteristics, including coverage in challenging data sets, the effect of RQ-RMI error bound, and training time.

5.1 Methodology

We ran the experiments on Intel Xeon Silver 4116 @ 2.1 GHz with 12 cores, 32KB L1-, 1024KB L2-, and 16MB L3- caches, running Ubuntu 16.04 (Linux kernel 4.4.0). We disable power management for stable measurements.

For evaluating each classifier we generated traces with 700K packets, accessing all matching rules uniformly to evaluate the worst-case memory access pattern. We processed the trace 6 times, using the first five as warmup and measuring the last. We report the average of 15 measurements.

**ClassBench rules.** ClassBench [34] is a standard benchmark broadly used for evaluating packet classification algorithms [2, 14, 19, 20, 26, 36, 39]. It creates rule-sets that correspond to the rule distribution of three different applications: Access Control List (ACL), Firewall (FW), and IP Chain (IPC). We created rule-sets of sizes 500K, 100K, 10K, and 1K, each with 12 distinct applications, all with 5-field rules: source and destination IP, source and destination port, and protocol.

**Real-world rules.** We used Stanford Backbone dataset which contains a large enterprise network configuration [41]. There are four IP forwarding rule-sets with roughly 180K single-field rules each (i.e., destination IP address).

**Evaluated configurations.** CutSplit (cs) is set with $\text{binth} = 8$, as suggested in [19].

For NeuroCuts (nc), we performed a hyperparameter sweep and selected the best classifier per rule-set. As recommended in [20], we focused on both top-mode partitioning and reward scaling. We ran the search on three 12-core Intel machines, allocating six hours per configuration to converge. In total, we ran nc training for up to 36 hours per rule-set. In addition, we developed a C++ implementation of nc for faster evaluation of the generated classifiers, much faster than the authors’ Python-based prototype.

TupleMerge (tm) is used with the version that supports updates with \texttt{collision-limit} = 40, as suggested in [2].

NuevoMatch (nm) was trained with a maximum error threshold of 64. We used two isets with cs and nc as a remainder, and four isets with tm. We discarded isets with coverage below 25% for comparisons against cs and nc, and below 5% for comparisons against tm. We present the analysis of the sensitivity to the chosen parameters and training times in §5.3.2.

5.2 End-to-end performance

We evaluated the performance using two cores. NuevoMatch allocates one core for the remainder computations and the second for the RQ-RMIs. For cs, nc and tm, we ran two instances of the algorithm in parallel on two cores using two threads (i.e., no duplication of the rules), splitting the input equally between the cores. We used batches of 128 packets to amortize the synchronization overheads. Thus, these algorithms achieve almost linear scaling and the highest possible throughput with perfect load-balancing between the cores.

For fair comparison, NuevoMatch used the same algorithm for both the remainder classifier and the baseline. For example, we evaluated the speedup produced by NuevoMatch over cs while also using cs to index the remainder set.

**Large rule-sets: ClassBench.** Figure 7 shows that, in the largest rule-sets (500K), NuevoMatch achieves a geometric factor of 2.7x, 4.4x, and 2.6x lower latency and 1.3x, 2.2x, and 1.2x higher throughput over cs, nc, and tm, respectively. For the classifiers with 100K rules, the gains are lower but still significant: 2.0x, 3.6x, and 2.6x lower latency and 1.0x, 1.7x, and 1.2x higher throughput over cs, nc, and tm, respectively. The performance varies among rule-sets, however. For example some classifiers are up to 1.8x faster than cs for 100K inputs.

**Large rule-sets: Stanford backbone.** Figure 8 shows the speedup of nm over tm for the real-world Stanford backbone dataset with 4 rule-sets. nm achieves 3.5x higher throughput and 7.5x lower latency over tm on all four rule-sets.

**Small rule-sets.** For rule-sets with 1K and 10K rules NuevoMatch results in the same or lower throughput, and 2.2x and 1.9x on average better latency compared to cs and tm. The lower speedup is expected as both cs and tm fit into L1 (§5.2.1), so nm’s reduced memory footprint does not yield performance advantages but adds computational overhead. See Appendix for the detailed chart.
The cs results are averaged over three rule-sets of 1K and six rule-sets for 10K. In the remaining rule-sets, NuevoMatch did not produce large-enough iSets to accelerate the remainder. Note, however, that it quickly identifies the rule-sets expected to be slow and falls back to the original classifier.

**The source of speedups.** The ability to compress the rule-set to fit into faster memory while retaining fast lookup is the key factor underlying the performance benefits of NuevoMatch. To illustrate it, we take a closer look at the performance. We evaluate \( \text{tm} \) with and without \( \text{nm} \) acceleration as a function of its memory footprint on a ClassBench-generated 1K, 10K, 100K and 500K rule-sets for one application (ACL).

Figure 9 shows that the performance of \( \text{tm} \) degrades as the number of rules grows, causing the hash tables to spill out of L1 and L2 caches. \( \text{nm} \) compresses a large part of the rule-set (see coverage), thereby making the remainder index small enough to fit it in the L1 cache, and gaining back the throughput \( \text{tm} \) had on small rule-sets.

**5.2.1 Memory footprint comparison.** Figure 10 compares the memory footprint of the classifiers without and with NuevoMatch (the two right-most bars in each bar cluster). We use the same number of iSets as in the throughput experiments. Note that smaller footprint alone does not necessarily lead to higher performance if more iSets are used. Therefore, the results should be considered in conjunction with the end-to-end performance.

The memory footprint includes only the index data structures but not the rules themselves. In particular, the memory footprint for NuevoMatch includes both the RQ-RMI models and the remainder classifier. Each bar is the average of all the 12 application rule-sets of the same size.

For \( \text{nm} \) we show both the remainder index size (middle bar) and the total RQ-RMI size (right-most bar). Note that due to the logarithmic scale of Y axis the actual ratio between the two is much higher than it might seem. For example, the remainder for 10K \( \text{tm} \) is almost 100× the size of the RQ-RMI. Note also that since we run \( \text{nm} \) on two cores, RQ-RMI and the remainder use their own CPU caches.

Overall, NuevoMatch enables dramatic compression of the memory footprint, in particular for 500K rule-sets, with 4.9×, 8×, and 82× on average over cs, nc and \( \text{tm} \) respectively.

The graph explains well the end-to-end performance results. For 1K rule-sets, the original classifiers fit into L1 cache, so \( \text{nm} \) is not effective. For 10K sets, even though the remainder index fits in L1, the ratio between L1 and L2 performance is not sufficient to cover the RQ-RMI computational overheads. For 100K, the situation is similar for cs; however, for nc, the remainder fits in L1, whereas the original nc spills to L3. For \( \text{tm} \), the remainder is already in L2, yielding lower overall speedup compared to nc. Last, for 500K rule-sets, all the original classifiers spill to L3, whereas...
Performance under L3 cache contention. Small memory footprint of \( n.m \) plays important role even when the rule-index fits in L3 cache (16MB in our machine). L3 is shared among all the CPU cores, therefore cache contention is not rare, in particular in data centers. \( n.m \) reduces the effects of L3 cache contention on packet classification performance. In the experiment we use the 500K rule-set (1) and compare the performance of \( c.s \) and \( n.m \) (with \( c.s \)) while limiting the L3 to 1.5MB. \( c.s \) looses half of its performance, whereas \( n.m \) slows down by 30%, increasing the original speedup.

### 5.3 Performance analysis

#### 5.3.1 iSet coverage

Table 2 shows the cumulative coverage achieved with up to 4 iSets averaged over 12 rule-sets (ClassBench) of the same size. The coverage of smaller rulesets is worse on average, but improves with the size of the rule-set.

The last row shows a representative result for Stanford backbone rule-set (the other three differ within 1%). Two iSets are enough to achieve 90% coverage and three are needed for 95%. This data set differs from ClassBench in that it contains only one field, providing fewer opportunities for iSet partitioning.

#### 5.3.2 Impact of the number of iSets

We seek to understand the tradeoff between the iSet coverage of the rule set and the computational overheads of adding more RQ-RMI.

### Table 2: iSet coverage.

| Number of iSets | 1 iSet | 2 iSets | 3 iSets | 4 iSets |
|-----------------|--------|---------|---------|---------|
| 1K              | 20.2 ± 18.6 | 28.9 ± 22.3 | 34.6 ± 25.6 | 38.7 ± 27.2 |
| 10K             | 45.1 ± 31.6 | 59.6 ± 38.9 | 62.6 ± 37.1 | 65.1 ± 35.7 |
| 100K            | 80.0 ± 14.5 | 96.5 ± 8.3   | 98.1 ± 4.8   | 98.8 ± 2.7   |
| 500K            | 84.2 ± 10.5 | 98.8 ± 1.5 | 99.4 ± 0.6 | 99.7 ± 0.2 |
|                 | 183,376 | 57.8     | 91.6     | 96.5     | 98.2     |

All computations were performed on a single core to obtain the latency breakdown. We use \( c.s \) for indexing the remainder.

Figure 11 shows the geomean of the coverage and the runtime breakdown over 12 rule-sets of 500K. The breakdown includes the runtime of the remainder classifier, validation, secondary search, and RQ-RMI inference. Zero iSets implies that \( c.s \) was run alone. Adding more iSets shows diminishing returns because of their compute overhead, which is not compensated by the remainder runtime improvements because the coverage is already saturated to almost 100%. Using one or two iSets shows the best trade-off. \( n.c \) shows similar results.

\( t.m \) behaved differently, however (not shown). \( t.m \) occupies much more memory than \( c.s \), therefore using more iSets to achieve higher coverage allowed to further speed up the remainder by fitting it into upper level cache. Thus, 4 iSets showed the best configuration.

We note that the runtime is split nearly equally between model inference and validation (which are compute-bound parts), and the secondary search and the remainder computations (which are memory-bound). We expect the compute performance of future processors to scale better than their cache capacity and memory access latency. Therefore, we believe \( n.m \) will provide better scaling than memory-bound state-of-the-art classifiers.

#### 5.3.3 Partitioning effectiveness

We seek to understand how low diversity rule-sets affect NuevoMatch. To analyze that, we synthetically generated a large rule-set as a Cartesian product of a small number of values per field (no ranges). We blended these rules into a 500K ClassBench-generated rule-set, replacing randomly selected rules with those from the Cartesian product, keeping the total size the same.

Table 3 shows the coverage and the speedup over \( t.m \) on the resulting mixed rule-sets for different fractions of low-diversity rules.

---

**Figure 10:** Memory size for CutSplit, NeuroCuts, TupleMerge vs. NuevoMatch with them indexing the remainder. Each bar is a geomean of 12 applications.

**Figure 11:** Coverage and execution time breakdown of NuevoMatch vs. varying number of iSets.
Table 3: Throughput and a single iSet coverage vs. the fraction of low-diversity rules in a 500K rule-set.

| % Low diversity rules | %Coverage | Speedup (throughput) |
|-----------------------|-----------|----------------------|
| 70%                   | 25%       | 1.07×                |
| 50%                   | 50%       | 1.14×                |
| 30%                   | 70%       | 1.60×                |

Figure 12: RQ-RMI training time in minutes vs maximum search range bound.

5.3.4 Training time and secondary search range. RQ-RMIs are trained to minimize the prediction error bound to achieve small secondary search distance. Recall that secondary search involves binary search within the error bound where each rule is validated to match all the fields.

The tradeoff between training time and secondary search performance is not trivial. Larger search distance enables faster training but slows down the secondary search. Smaller search distance results in faster search but slows down the training. In extreme cases, the training does not converge since higher precision might require larger submodels. However, increasing the size of the submodels leads to a larger memory footprint and longer computations.

Figure 12 shows the average training time in minutes of 500 models as a function of the secondary search distance and the rule-set size. As mentioned (§4), our training implementation can be dramatically accelerated, so the results here indicate the general trend.

Training with the bound of 64 is expensive, but is it really necessary? To answer, we evaluate the performance impact of the search distance on the secondary search time. We measure 40ns for retrieving a rule with a precise prediction (no search). For 64, 128 and 256 distances the search time varies between 75 to 80ns thanks to binary search. Last, it turns out that the actual search distance from the predicted index is often much smaller than the worst-case one enforced in training. Our analysis shows that in practice, training with a relatively large bound of 128 leads to 80% of the lookups result with a search distance of 64, and 60% with 32.

We conclude that training with larger bounds is likely to have a minor effect on the end-to-end performance, but significantly accelerate training. This property is important to support more frequent retraining and faster updates (§3.9).

5.3.5 Performance with more fields. Adding fields to an existing classifier will not harm its coverage, so it will not affect the RQ-RMI performance. Nonetheless, more fields will increase validation time.

Unfortunately we did not find public rule-sets that have a large number of fields. Thus we run a microbenchmark by increasing the number of fields and measuring the validation stage performance. As expected, we observe almost perfectly linear growth in the validation time, from 25ns for one field to 180ns for 40 fields.

6 RELATED WORK

Hardware-based classifiers. Hardware-based solutions for classification such as TCAMs and FPGAs achieve a very high throughput [5, 30]. Consequently, many software algorithms take advantage of them, further improving classification performance [12, 18, 21, 22, 26, 28, 32]. Our work is complementary, but can be used to improve scaling of these solutions. For example, if the original classifier required large TCAMs, the remainder set would fit much smaller TCAM.

GPUs for classification. Accelerating classification on GPUs was suggested by numerous works. PacketShader [9] uses GPU for packet forwarding and provides integration with Open vSwitch. However, packet forwarding is a single-dimensional problem, so it is easier than multi-field classification [8]. Varvello et al. [37] implemented various packet classification algorithms in GPUs, including linear search, Tuple Space Search, and bloom search. Nonetheless, these techniques suffer from poor scalability for large classifiers with wildcard rules which NuevoMatch aims to alleviate.

ML techniques for networking. Recent works suggest using ML techniques for solving networking problems such as TCP congestion control [3, 11, 40], resource management [23], quality of experience in video streaming [24, 38], routing [35], and decision tree optimization for packet classification [20]. NuevoMatch is different in that it uses an ML technique for building space-efficient representations of the rules that fit in the CPU cache.

7 CONCLUSIONS

We presented NuevoMatch, the first packet classification technique that uses Range-Query RMI machine learning
model for accelerating packet classification. We have shown an efficient way of training RQ-RMI models, making them learn the matching ranges of large rule-sets, via sampling and analytical error bound computations. We demonstrated the application of RQ-RMI to multi-field packet classification using rule-set partitioning. We evaluated NuevoMatch on synthetic and real-world rule-sets and confirmed its benefits for large rule-sets over state-of-the-art techniques.

NuevoMatch introduces a new point in the design space of packet classification algorithms and opens up new ways to scaling it on commodity processors. We believe that its compute-bound nature and the use of neural networks will enable further scaling with future CPU generations, which will feature powerful compute capabilities targeting faster execution of neural network-related computations.

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We term the input domain of an RQ-RMI model as \( D \subset \mathbb{R} \) and its number of stages as \( n \). The following theorem suggests a fast and efficient way for accurately calculating the responsibilities of any of its submodels:

**Theorem A.1 (Responsibility Theorem).** Let \( s_i \) be a trained stage such that \( i < n - 1 \). The responsibilities of submodels in \( s_{i+1} \) can be calculated by evaluating a finite set of inputs over the stage \( s_i \).

The intuition behind Theorem A.1 is based on Corollary 3.2, namely that submodels output piecewise linear functions. Proving it requires some additional definitions. First, we formally define two of the theorem’s components: (1) a stage output, and (2) submodel responsibility:

**Definition A.2 (Stage Output).** The output of stage \( s_i \) is defined for \( x \in D \) as \( S_i(x) = M_{i,i}(x) \) where \( f_i(x) \) is the index of the submodel in \( s_i \) that is responsible for input \( x \), and defined as

\[
\begin{align*}
  f_i(x) &= \begin{cases} 
    0 & i = 0 \\
    \left[S_{i-1}(x) \cdot W_i\right] & i = \{1, 2, \ldots, n-1\}
  \end{cases}
\end{align*}
\]

**Definition A.3 (Submodel Responsibility).** The responsibility of a submodel \( M_{i,j} \) is defined as

\[
R_{i,j} = \begin{cases} 
  D & i = 0 \\
  \{x \mid f_i(x) = j\} & i = \{1, 2, \ldots, n-1\}
\end{cases}
\]

Note that the responsibilities of every two submodels in the same stage are disjoint.

Second, we define the left and right slopes of a point in a piecewise linear function.

**Definition A.4 (Left and Right Slopes).** For a range \( R \), if points \( \min_{x \in R} x \) or \( \max_{x \in R} x \) are defined, we refer to them as the boundaries of the range. For all other points, we refer as internal points of the range. For a piecewise linear function defined over some range \( R \), for every internal point \( x \in R \), there exists \( \delta > 0 \) such that the function is linear in each of \( (x-\delta, x) \), \( (x, x+\delta) \). Accordingly, we can refer to the left slope and the right slope of a point, defined as those of the two linear functions.

Third, we make two observations on the input domain \( D \) that enable us not only proving Theorem A.1 but finding the finite set of inputs that lead to calculating the submodels’ responsibilities.

**Definition A.5 (Trigger Inputs).** We say that an input \( g \in D \) is a trigger input of a submodel \( M_{i,j} \) if one of the following holds: (i) \( g \) is a boundary point of \( D \) (namely, \( g = \min_{y \in D} y \) or \( g = \max_{y \in D} y \)). (ii) \( g \) is an internal point of \( D \) and the left and right slopes of \( M_{i,j}(g) \) differ.

**Definition A.6 (Transition Inputs).** We say that an input \( t \in D \) is a transition input of a submodel \( M_{i,j} \) if it changes submodel selection in the following stage. Formally, there exists \( \epsilon > 0 \) such that for all \( 0 < \delta < \epsilon \):

\[
[M_{i,j}(t-\delta) \cdot W_{i+1}] \neq [M_{i,j}(t+\delta) \cdot W_{i+1}]
\]

**Definition A.7 (The function \( B_i(x) \)).** For readability, we define the function \( B_i \) for \( i \in \{0, 1, \ldots, n-1\} \), \( B_i \) is a staircase function of values \( [0, W_{i+1} - 1] \), and defined as

\[
B_i(x) = [x \cdot W_{i+1}] \text{ for } x \in [0, 1).
\]
For a submodel $m_{i,j}$, we term the set of its trigger inputs as $G_{i,j}$ and the set of its transition inputs as $T_{i,j}$. See Figure 13 for illustration. From submodel definition and Corollary 3.2, we can tell that a submodel’s ReLU operations determine its trigger inputs. Consequently, any set of trigger inputs is finite and can be calculated using a few linear equations. Nonetheless, calculating the transition inputs of a submodel is not straightforward. We show a fast and efficient way for doing so in the following lemma:

**Lemma A.8.** Let $m_{i,j}$ be an RQ-RMI submodel, and $a < b \in G_{i,j}$ two adjacent trigger inputs of $m_{i,j}$. Then the set $S = [a,b] \cap T_{i,j}$ is finite and can be calculated using the inputs $a$ and $b$ alone.

**Proof.** We divide the construction of $S$ to two subsets $S = S_0 \cup S_1$. First we handle $S_0$. For each $x \in [a,b]$, $x \in S_0$ if and only if there exists $\epsilon > 0$ such that for all $0 < \delta < \epsilon$:

$$B_i(M_{i,j}(x - \delta)) \neq B_i(M_{i,j}(x + \delta))$$

Now to $S_1$. Without loss of generality, $M_{i,j}(a) \leq M_{i,j}(b)$. From Corollary 3.2 and Definition A.5, $M_{i,j}$ is linear in $[a,b]$. If $B_i(M_{i,j}(a)) = B_i(M_{i,j}(b))$, then $S_1 = \emptyset$. Otherwise, $M_{i,j}(a) \neq M_{i,j}(b)$. $B_i(x)$ outputs discrete values between $B_i(M_{i,j}(a))$ and $B_i(M_{i,j}(b))$ for all $x \in (a,b)$. Denote this finite set of discrete values as $M$. For any $y \in M$ there exists a value $d \in (a,b]$ such that $M_{i,j}(d) - W_{i+1} = y$. By the linearity of $M_{i,j}$ in $[a,b]$:

$$d = \left(\frac{y}{W_{i+1} - M_{i,j}(a)}\right) \cdot \frac{b - a}{M_{i,j}(b) - M_{i,j}(a)} + a$$

We construct a $S_1$ as follows:

$$S_1 = \left\{ \left(\frac{y}{W_{i+1} - M_{i,j}(a)}\right) \cdot \frac{b - a}{M_{i,j}(b) - M_{i,j}(a)} + a \mid \forall y \in M \right\}$$

**Corollary A.9.** The set of transition inputs $T_{i,j}$ can be calculated using $G_{i,j}$ and its size is bounded such that $|T_{i,j}| \leq W_{i+1} \cdot |G_{i,j}|$.

Not all transition inputs of all submodels are reachable, as some exist outside of their corresponding submodel’s responsibility. Therefore, we define the set of reachable transition inputs of a stage $s_i$ as the transition set of a stage:

**Definition A.10 (Transition Set).** The transition set $U_i$ of a stage $s_i$ is an ordered set, defined as:

$$U_i = \{\min(D)\} \cup \{\bigcup_{j=0}^{W_{i-1}} T_{i,j} \cap R_{i,j}\} \cup \{\max(D)\}$$

The proof of Theorem A.1 directly follows from the next two lemmas:

**Lemma A.11.** Let $s_i, s_{i+1}$ be two adjacent stages. For any two adjacent values $u_0 < u_1 \in U_i$ there exists a submodel $m_{i+1,j}$ such that $S_{i+1}(x)$ is piecewise linear and equal to $M_{i+1,j}(x)$ for all $x \in (u_0, u_1)$.

**Proof.** We show that there exists a submodel $m_{i+1,j}$ such that any $x \in (u_0, u_1)$ satisfies $x \in R_{i+1,j}$, which implies $f_{i+1}(x) = j$ and so $S_{i+1}(x) = M_{i+1,j}(x)$. By Corollary 3.2 $S_{i+1}$ is piecewise linear for all $x \in (u_0, u_1)$.

Let $x < y \in (u_0, u_1)$. Assume by contradiction there exist two submodels $m_{i+1,j_1}$ and $m_{i+1,j_2}$ such that $x \in R_{i+1,j_1}$ and $y \in R_{i+1,j_2}$. From Definition A.5, $f_{i+1}(x) \neq f_{i+1}(y)$ implies $B_i(S_{i}(x)) \neq B_i(S_i(y))$. Thus, there exists an input $z \in (x,y)$ and $\epsilon > 0$ such that for all $0 < \delta < \epsilon$:

$$B_i(S_i(z - \delta)) \neq B_i(S_i(z + \delta))$$

Since $S_i$ consists of the outputs of submodels in $s_i$, there exists a submodel $m_{i,k}$ such that $S_i(z) = M_{i,k}(z)$. Therefore, $z \in T_{i,k}$ and $z \in R_{i,k}$, which means $z \in U_i$. Contradiction to definition of $u_0$ and $u_1$.

**Lemma A.12.** Let $s_i$ be an RQ-RMI stage such that $i \in \{0, 1, ..., n-2\}$. The function $f_{i+1}$ defined over the space $D$ can be calculated using the inputs $U_i$ over $s_i$.

**Proof.** Let $u_0 < u_1 \in U_i$ be two adjacent values. By Lemma A.11 there exists a submodel $m_{i+1,j}$ such that $S_{i+1}(x) = M_{i,j}(x)$ for all $x \in (u_0, u_1)$. From Definition A.2, $f_{i+1}(x) = j$ for all $x \in (u_0, u_1)$. By calculating $B_i(S_i(u_0))$ and $B_i(S_i(u_1))$, $f_{i+1}(x)$ is known for all $x \in [u_0, u_1]$. Since $\min(D) \in U_i$ and $\max(D) \in U_i$, $f_{i+1}(x)$ is known for all $x \in D$.

## A.2 Submodel prediction error

**Theorem A.13 (Submodel Prediction Error).** Let $s_{n-1}$ be the last stage of an RQ-RMI model. The maximum prediction error of any submodel in $s_{n-1}$ can be calculated using a finite set of inputs over the stage $s_{n-1}$.

The intuition behind Theorem A.13 is addressing the set of range-value pairs as an additional, virtual, stage in the model. Intending to prove that theorem, we start by providing a formal definition of range-value pairs.

**Definition A.14 (Range-Value Pair).** A range-value pair $(r,v)$ is defined such that $r$ is an interval in $D$ and $v \in \{0, 1, 2, ..., \}$ is unique to that pair.

We term $W_n$ the number of range-value pairs an RQ-RMI model should index. Similar to the definitions for submodels, we extend $f_i$ such that $f_n(x) = [S_{n-1}(x) \cdot W_n]$, and say that the responsibility $R_p$ of a pair $p = (r,v)$ is the set of inputs $\{x : f_n(x) = v\}$. Consequently, we make the following two observations. First, all inputs in the range $r \setminus R_p$ should have reached $p$ but did not. Second, all inputs in the range $R_p \setminus r$ did reach $p$ but should not.
**Definition A.15 (Misclassified Pair Set).** Let $m$ be a submodel in $s_{n-1}$ with a responsibility $R_m$. Denote $P_m$ as the set of all pairs such that a pair $p = (r, v) \in P_m$ satisfies $(r \setminus R_p) \cup (R_p \setminus r) \cap R_m \neq \emptyset$. In other words, $P_m$ holds all pairs that were misclassified by $m$, and termed the misclassified pair set of $m$.

We are now able to define the maximum misprediction of an RQ-RMI submodel.

**Definition A.16 (Maximum Prediction Error).** Let $m$ be a submodel in $s_{n-1}$ with a responsibility $R_m$ and a misclassified pair set $P_m$. The maximum prediction error of $m$ is defined as:

$$\max \{|f_m(x) - v| \mid (r, v) \in P_m, x \in R_m\}$$

We prove Theorem A.13 using the following lemma:

**Lemma A.17.** The misclassified pair sets of all submodels in $s_{n-1}$ can be calculated using $U_{n-1}$ over $S_{n-1}$.

**Proof.** Let $q_0 < q_1$ be two adjacent values in $U_{n-1}$. From Lemma A.11 there exists a single submodel $m_{n-1, j}, j \in W_{n-1}$ such that $S_{n-1}(x) = M_{n-1, j}(x)$ for all $x \in (q_0, q_1)$. Hence, using Corollary 3.2, $S_{n-1}$ is linear in $(q_0, q_1)$. Therefore, the values of $S_{n-1}$ in $[q_0, q_1]$ can be calculated using $q_0$ and $q_1$ alone. Consequently, according to the definitions of $f_m$ and the responsibility of a pair, the set of pairs $P_j$ with responsibilities in $[q_0, q_1]$ can also be calculated using $q_0$ and $q_1$. Calculating the responsibilities of all pairs is performed by repeating the process for any two adjacent points in $U_{n-1}$.

At this point, as we know $R_p$ for all $p = (r, v)$, calculating the set $(r \setminus R_p) \cup (R_p \setminus r)$ is trivial. Acquiring the responsibility of any submodel in $s_{n-1}$ using Theorem A.1 enables us calculating its misclassified pair set immediately.

**Proof of Theorem A.13.**

Let $m$ be a submodel in $s_{n-1}$ with a responsibility $R_m$. For simplicity, we address the case where $R_m$ is a continuous range. Extension to the general case is possible by repeating the proof for any continuous range in $R_m$.

Denote the submodel’s finite set of trigger inputs as $G_m$. Define the set $Q$ as follows:

$$Q = \min R_m \cup (G_m \cap R_m) \cup \max R_m$$

Let $q_0 < q_1$ be two adjacent values in $Q$. From definition of trigger inputs, $m$ outputs a linear function in $[q_0, q_1]$. Hence, the set of values $S_0 = \{f_m(x) \mid x \in [q_0, q_1]\}$ can be calculated using only $q_0$ and $q_1$ over $S_{n-1}$. From Lemma A.17, the misclassified pair set $P_m$ can be calculated using the finite set $U_{n-1}$. Denote the set

$$\hat{P}_0 = \{ (r, v) \mid (r, v) \in P_m, r \cap [q_0, q_1] \neq \emptyset\}$$

Calculating $\max \{s - v \mid s \in S_0, (r, v) \in \hat{P}_0\}$ yields the maximum error of $m$ in $[q_0, q_1]$. Repeating the process for any two adjacent points in $Q$ yields the maximum error of $m$ for all $R_m$.

**Rule-set names** in Figures 7 and 14, by order: ACL1, ACL2, ACL3, ACL4, ACL5, FW1, FW2, FW3, FW4, FW5, IPC1, IPC2.

**Table 4: RQ-RMI configurations for different input rule-set sizes.**

| #Rules   | #Stages | Stage Widths   |
|----------|---------|----------------|
| Less than $10^3$ | 2       | [1, 4]         |
| $10^3$ to $10^4$ | 3       | [1, 4, 16]     |
| $10^4$ to $10^5$ | 3       | [1, 4, 128]    |
| More than $10^5$ | 3       | [1, 8, 256] or [1, 8, 512] |