Branch Prediction Is Not A Solved Problem: Measurements, Opportunities, and Future Directions

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***Abstract*—Modern branch predictors predict the vast majority of conditional branch instructions with near-perfect accuracy, allowing superscalar, out-of-order processors to maximize speculative efficiency and thus performance. However, this impressive overall effectiveness belies a substantial missed opportunity in single-threaded instructions per cycle (IPC). For example, we show that correcting the mispredictions made by the state-of-the-art TAGE-SC-L branch predictor on SPECint 2017 would improve IPC by margins similar to an advance in process technology node.**

In this work, we measure and characterize these mispredictions. We find that they categorically arise from either (1) a small number of systematically hard-to-predict (H2P) branches; or (2) rare branches with low dynamic execution counts. Using data from SPECint 2017 and additional large code footprint applications, we quantify the occurrence and IPC impact of these two categories. We then demonstrate that solely increasing the resources afforded to existing branch predictors does not address the root causes of most mispredictions. This leads us to reexamine basic assumptions in branch prediction and to propose new research directions that, for example, deploy machine learning to improve pattern matching for H2Ps, and use on-chip phase learning to track long-term statistics for rare branches.

I. Introduction

Branch prediction is critical to the performance of modern superscalar processors [1], [2], [3] and is implemented in dedicated branch prediction units (BPUs). BPUs work by training statistical models of branch directions observed as instructions are retired, and then using these models to predict unresolved directions for subsequent branches, as they are fetched. BPU predictions drive speculative execution, a key technique for hiding latency in out-of-order CPUs.

Though state-of-the-art branch predictors achieve near-perfect prediction accuracy on the vast majority of static branches, substantial performance gains can be unlocked by correcting their remaining mispredictions. Mispredictions delay subsequent instructions, trigger instruction pipeline flushes, and reduce speculation efficiency. For example, Fig. 1 shows single-threaded performance for the SPECint 2017 benchmarks on an execution pipeline based on Intel Skylake, as we simulate future designs with increased pipeline capacity (i.e., fetch, decode, execution, load/store buffer, ROB, scheduler, and retire resources) in the ChampSim simulator [4], [5]. Using the TAGE-SC-L 8KB branch predictor [6], mispredictions represent an 18.5% instructions per cycle (IPC) opportunity at baseline (1x scaling). This gain grows with pipeline scale, e.g., to 55.3% at 4x scaling, a magnitude on par with advancing to the next process technology node.

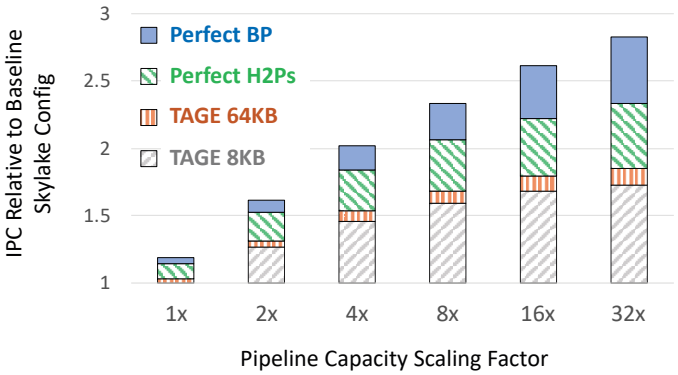

Fig. 1: Without better branch prediction, scaling the pipeline capacity of an Intel Skylake configuration will produce diminishing returns in single-threaded IPC for SPECint 2017.

Microarchitectural advances in branch prediction are thus a source of large potential IPC gains. However, we find only marginal improvements from straightforward scaling of the resources provided to existing predictors. Fig. 1 illustrates this point: increasing TAGE-SC-L storage eight-fold to 64KB returns just 2.7% additional IPC in a best-case scenario where no additional prediction latency is incurred due to larger table sizes.

In this paper, we perform a deep dive into the causes of these mispredictions, and demonstrate that fundamentally new approaches to branch prediction are needed to address them. We identify two primary issues: (1) systematically hard-to-predict (H2P) branches; and (2) rare branches with low dynamic execution counts over tens of millions of instructions. In addition to degrading IPC, these branches trigger inefficient consumption of BPU storage on a large scale, and exhibit temporal behaviors inconsistent with the short-term statistics emphasized in known algorithms. We propose new approaches that deploy powerful machine learning models to improve the pattern matching that drives H2P predictions (e.g. using low-precision convolutional neural networks, as developed in our companion paper [7]), as well as on-chip phase recognition to capture long term predictive statistics.

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II. Current State of the Art

We begin our analysis by reviewing the state of the art in branch prediction. Over prior decades, the Championship Branch Prediction (CBP) challenge [3] has served as the primary platform to compare techniques using common benchmarks and deployment assumptions. For example, submissions to the most recent CBP held in 2016 were run on a simulator that (1) standardized the inputs to the BPU to include the instruction pointer (IP) value, the instruction type, the branch target, and the observed direction for conditionals; and (2) restricted BPU storage to 8KB or 64KB, but imposed no restriction on prediction latency. These assumptions are compatible with ChampSim, which we use to close the loop from prediction accuracy to core IPC for CBP2016 submissions.

Depending on the algorithm, BPUs typically organize raw data into three modalities: (1) the *global branch history* [8], which is an ordered sequence of recently executed branch directions at any point in a program; (2) each branch's *local history* [9], which is the ordered sequence of directions taken by that branch in the past; and (3) the *path history*, which consists of the IP values from recent branches. CBP2016 submissions model this data using the following algorithms:

Partial Pattern Matching (PPM) [10], [11] compares a sequence of data against previously observed sequences of increasing length, and returns the longest exact match. A PPM branch predictor is implemented by hashing history data over various lookback windows into tagged table entries that track directions with a saturating counter. PPM predictors achieve best performance when many history lengths are tracked, and both the number of lengths and the number of table entries used per length are the primary drivers of their storage/accuracy tradeoff.

Perceptron Predictors mitigate a shortcoming of PPM's exact pattern matching by learning weights on different history positions [12], [13]. This improves accuracy when two branches' directions are correlated by damping *uncorrelated* history data. For PPM, uncorrelated or noisy history data explodes the number of unique sequences associated with branch statistics; perceptron predictors more compactly capture correlations by instead training and storing positional weights. At prediction time, weights are multiplied by a global history sequence, summed, and thresholded to generate a prediction.

Domain-Specific Models fit BPU data to templates of program execution behavior. Examples include loop predictors that predict exit conditions [14], the Wormhole predictor and Inner-Most Loop Iteration counter (IMLI) that track correlations between branches in nested loops [15], [16], and the Store/Load Predictor, which tracks data dependencies affecting branch conditions [17]. These predictors are derived from detailed expert analysis, and target specific program behaviors found to cause mispredictions in design-time benchmarks.

Ensemble Models generate a single prediction from multiple trained models, implementing a form of *boosting*. For example, the *statistical corrector* uses a perceptron-like model to apply weights to predictions of constituent predictors.

TAGE-SC-L is the CBP2016 winner, and we focus on it in this paper. It implements an ensemble predictor that combines PPM predictions from histories whose lengths follow a geometric-series (TA**GE**) with the IMLI loop predictor (**L**). The statistical corrector (**SC**) arbitrates between available predictions.

III. Misprediction Characteristics

Below, we describe the two datasets we used to quantify mispredictions.

A. H2P branches in SPECint 2017

We primarily used traces of SPECint 2017 benchmarks to study H2Ps. This dataset was constructed by first compiling each SPECint 2017 benchmark in the single-threaded "SPEC-speed" configuration, and then tracing the resulting binaries over multiple application inputs (i.e., "workloads"). Similar to Amaral *et al.* [18], we expanded the set of application inputs (see Table I) for each benchmark in order to capture greater diversity in program statistics and invariant behaviors across distinct application inputs. Each workload was traced for 10B instructions, which we post-processed into 30M-instruction slices; this slice length matches the default granularity of SimPoint phase labeling and maintains consistency with prior analyses [19]. The slices were then clustered via SimPoint [20] and labeled accordingly. Doing so verifies that our 10B-instruction trace length captures a variety of distinct application phases (9.2 phases, on average). However, we emphasize that the branch misprediction statistics shown in Table I are *not* collected from just the SimPoints, but across all 30M-instruction slices of each workload trace (i.e., 333 slices total for each 10B-instruction workload trace). This methodology helps capture stable statistics over time, i.e., over multiple occurrences of the phases.

Within each 30M-instruction slice of every workload, we screen branches and identify as H2Ps those that (1) have less than 99% prediction accuracy under TAGE-SC-L 8KB, (2) execute at least 15,000 times, and (3) generate at least 1,000 mispredictions in the slice. Our screening criteria are chosen to identify branches that exhibit behaviors consistent with systematic misprediction, and that produce sufficient history data to train machine learning models [7]. We screen using TAGE-SC-L 8KB because it represents a practical implementation of the state-of-the-art under common CPU resource budgets that we encounter today; in Section IV, we present a limit study of scaling up TAGE-SC-L resources and its effect on H2Ps.

The branch statistics shown in Table I convey two important messages. First, there exist a small number of H2Ps that consistently produce mispredictions every time the application executes—on average, 23 H2Ps appear in three or more workloads per benchmark. These H2Ps present a clear target for specialized prediction mechanisms. Second, over all workloads, 48.6% of the mispredictions in each 30M-instruction slice are caused by just 6 H2Ps, on average. Fig. 2 plots

SPECint2017 Benchmark	Avg # Phases	# Static Branches		Avg. Acc.	Avg. Acc. excl. H2Ps	# App. Inputs	H2P Appearance Across Inputs		# Static H2P Branches		Avg. Dyn. Execs per H2P per Slice	% Mispreds due to H2Ps per Slice
		Total	Median per Slice				Total	3+ Inputs	Avg per Input	Avg per Slice		
600.perlbench_s	6.5	13,865	1,863	0.987	0.989	4	62	16	21.5	1	93,815	17.3%
605.mcf_s	11.4	1,755	99	0.921	0.998	8	29	20	19.0	10	249,195	96.9%
620.omnetpp_s	11.8	7,099	823	0.975	0.994	5	46	28	28.0	8	74,630	77.6%
623.xalancbmk_s	7.5	8,563	3,103	0.997	0.998	4	28	8	14.5	6	75,329	28.6%
625.x264_s	13.9	4,892	1,068	0.946	0.975	14	23	7	6.0	1	65,593	54.2%
631.deepsjeng_s	9.4	3,162	856	0.946	0.963	12	68	49	40.0	13	44,412	31.2%
641.leela_s	8.8	3,623	582	0.880	0.960	10	77	68	56.5	34	35,614	66.4%
648.exchange2_s	8.4	3,765	1,330	0.986	0.992	5	38	19	20.0	7	142,320	44.7%
657.xz_s	7.6	2,373	211	0.897	0.980	5	163	50	63.0	10	75,759	80.5%
GEOMEAN	9.2	4,489	745	0.95	0.99	7	49	23	24.2	6	80,814	48.6%

TABLE I: Summary statistics of our SPECint 2017 data set, which includes an expanded collection of inputs for each benchmark. Metrics are averaged over 10B-instruction traces from each input. Accuracy and H2P statistics are reported for TAGE-SC-L 8KB.

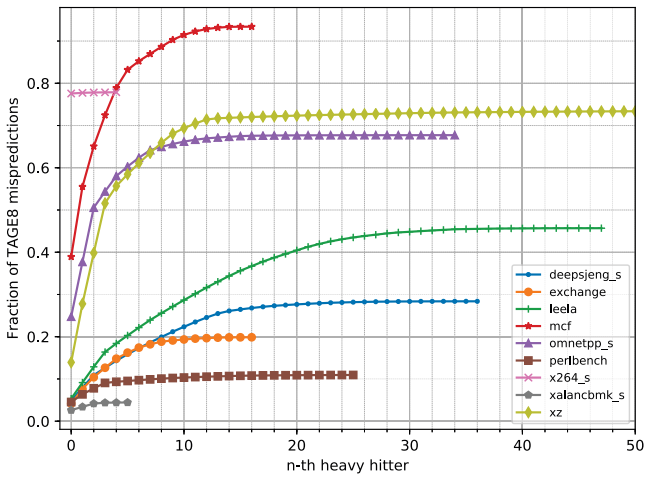


Fig. 2: Cumulative fraction of mispredictions due to H2Ps for SPECint 2017 benchmarks. The top five "heavy hitters" account for 37% of dynamic mispredictions on average.

the cumulative fraction of mispredictions for H2Ps in each benchmark ranked by total number of dynamic executions. We see that the top five in their respective benchmarks account for 37% of dynamic mispredictions on average, and dub these "heavy-hitters." Taken together, this means that *just a handful of static branches cause a disproportionately large number of dynamic mispredictions*, and that devoting resources to improve their prediction accuracy is an attractive strategy for increasing performance.

B. Rare branches in large code footprint (LCF) traces

Table I excludes 603.gcc_s because we notice that its much larger code footprint includes many more branches that make small but significant contributions to overall mispredictions. To study this effect further, we collected a set of similarly large code footprint (LCF) traces.

LCF binaries all have many more static branch IPs per 30M-instruction slice than our SPECint 2017 dataset, as shown by comparing Table I to Table II. We chose applications with static branch counts above that of SPEC 2017

Application	Static Branch IPs	Avg. Dyn. Execs per Static Branch	Avg. Acc. per Static Branch	H2Ps
602.gcc_s	6,152	715.6	0.88	5
Game	45,996	55.2	0.73	1
RDBMS	16,096	314.3	0.92	8
NoSQL Database	7,449	331.0	0.93	2
Real-time Analytics	5,595	856.0	0.83	6
Streaming Server	3,144	1404.7	0.78	6
GEOMEAN	9,175	412.7	0.84	3.8

TABLE II: Summary branch statistics from large code footprint applications under TAGE-SC-L 8KB. Metrics shown are over 30M-instruction traces.

623.xalancbmk_s, the next largest footprint after 603.gcc_s. In addition to 603.gcc_s, we include five additional applications (a game, a RDBMS, a NoSQL database, a real-time analytics engine, and a streaming server) which were traced from live deployments. For these, we analyze a single 30M-instruction trace for each application. Though less comprehensive than the SPEC2017 dataset, this is nonetheless sufficient to illustrate the rare branch problem in large code footprints.

Table II summarizes branch statistics for the LCF applications. There are two observations of note: (1) the average accuracy of TAGE-SC-L 8KB for these applications is significantly lower (0.84) than for the SPECint 2017 dataset (0.95); (2) for the large number of static branches in each application (geomean: 9,175), the average number of dynamic executions per static branch is small (geomean: 412.7). Fig. 3 further breaks out these summary statistics into distributions of branches over the entire dataset. As we can see, the distribution of dynamic executions (middle) skews towards the left, with fully 85% of static branch IPs executing less than 100 times. Additionally, the distribution of dynamic mispredictions (left) skews towards zero, i.e., the vast majority of branches are predicted with high accuracy. This is corroborated by the distribution of prediction accuracy (right), where 55% of branches are predicted with 0.99 accuracy or greater. Yet, there is a significant fraction (12%) of static branch IPs which are

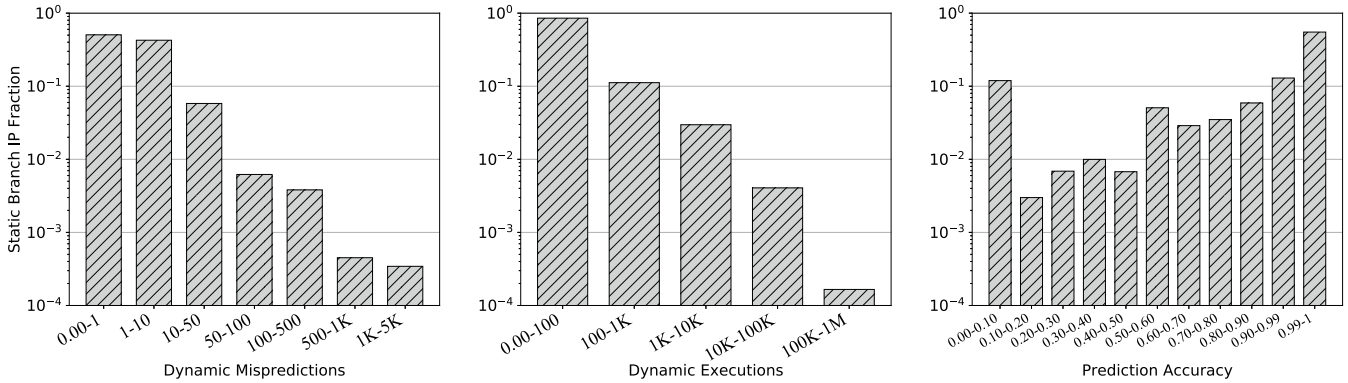
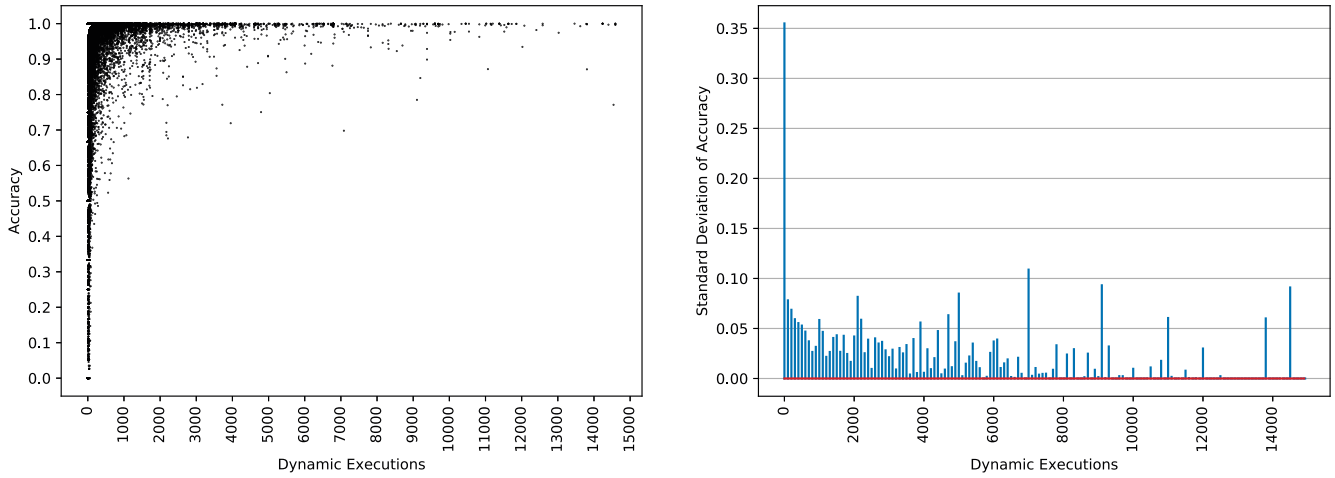


Fig. 3: The distributions of dynamic mispredictions (left), dynamic executions (middle), and prediction accuracy (right) of branches in the LCF data set, under TAGE-SC-L 8KB.



(a) (b)

Fig. 4: (a) For the LCF dataset, branches with low dynamic execution count have a wide spread in prediction accuracy under TAGE-SC-L 8KB. Each data point is a branch. (b) Standard deviation of branches binned by dynamic execution count.

predicted with an accuracy of 0.10 or lower.

Fig. 4a plots dynamic execution count against prediction accuracy for each static branch IP. This shows that *rare branches*, i.e., those with low dynamic execution counts, have a wide spread in prediction accuracy. In a sense, this is unsurprising because rare branches have fewer samples of path and direction history and thus their collected statistics are lower-confidence. Fig. 4b quantifies this spread, showing the standard deviation in prediction accuracy when we bin dynamic executions (bin width = 100). The first bin, with less than 100 dynamic executions, has a standard deviation in accuracy of 0.35, but this drops off precipitously to just 0.08 for branches with 100–200 dynamic executions.

In summary, LCF applications have many rare branches, which are static branches that are predicted poorly, but execute only a handful of times and thus do not meet the H2P criteria as a source of systematic misprediction. We also note that both scenarios are present in the above datasets, but to varying degrees—the SPECint 2017 dataset showcases H2Ps more than rare branches, whereas the opposite is true for the LCF dataset.

C. The effect of CPU pipeline scaling on mispredictions

One key observation is that H2Ps and rare branches do not have equal impact on performance when the CPU pipeline is scaled up, e.g., in future cores. Fig. 1 shows that, for the smaller code footprint applications in SPECint 2017, H2Ps account for 75.7% of the potential IPC gain of perfect branch prediction at baseline. When the pipeline is scaled up, the proportion shifts to near parity, with H2Ps accounting for 54.8% of the opportunity. For the LCF dataset, non-H2P rare branches play the central role, as shown in Fig. 5. At the baseline 1x pipeline scale, H2Ps represent just 37.8% of the performance opportunity, and this even drops slightly to 33.7% at 32x pipeline scale. Together, this data shows that *while H2Ps represent an outsized portion of the IPC*

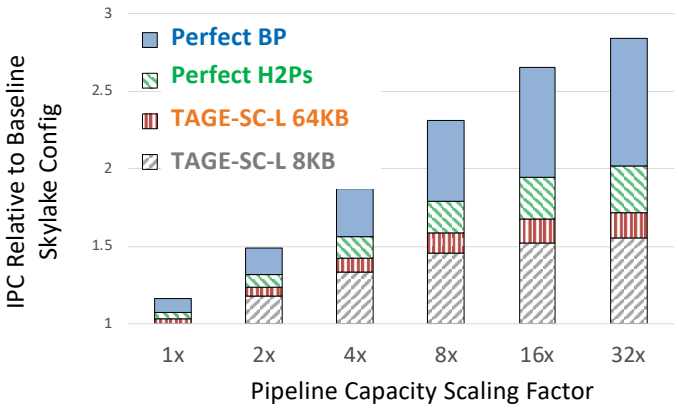


Fig. 5: For the large code footprint traces, H2Ps play a dramatically diminished role as CPU pipeline scales up.

impact for SPECint 2017 on existing CPUs, as pipelines scale and application sizes grow, rare branches become an equally important source of potential performance.

IV. Scaling BPU Resources is Not Enough

Aside from the practical limitations imposed by area and latency constraints [21], simply increasing BPU resources is insufficient to capture the sizable remaining IPC opportunity due to branch mispredictions. As we saw earlier, for a given CPU pipeline width and depth, scaling TAGE-SC-L global history table sizes, e.g., from 8KB to 64KB, as in Fig. 1, gives poor returns. We next analyze the reasons for this behavior.

A. H2Ps have high history variation

TAGE-SC-L 64KB tracks branch histories with lengths up to 3,000 (TAGE-SC-L 8KB allows up to 1,000). However, we show that longer history lengths inject *more* variation into the predictive signatures. We characterize this variation by analyzing an H2P's *dependency branches*, i.e., previously-retired branches whose conditions share an operand with the H2P, and are therefore predictive at ground truth. For a dynamic execution of an H2P, we compute its operand dependency graph over the prior 5,000 instructions. This graph links instructions that read a common piece of data by tracking chains of reads/writes to memory and registers. We identify as a dependency branch any prior conditional branch instruction that reads a data value that is also read when computing the H2P's condition. For each H2P, we perform this analysis for all of its dynamic executions over the entire trace to produce a distribution over the history positions of predictive dependency branches as they appear to the BPU.

Table III shows the min and max history positions of these distributions and the number of dependency branches for the top H2P heavy hitter of each SPECint 2017 benchmark. We observe that the maximum history lengths across all benchmarks fall within the history length limit of TAGE-SC-L 64KB. This suggests that TAGE-SC-L 64KB has sufficient history to predict the H2P, but that other factors contribute to its poor prediction accuracy. In Fig. 6, we plot the distributions of history positions for dependency branches associated with each heavy hitter. Notably, we see that any given dependency branch appears in many different positions, and that the likelihood of it again appearing in the same position is highly non-uniform. Together, this data shows that predictions based on position-specific correlations or the recurrence of exact patterns must contend with an enormous amount of stochastic variation, and that variation increases with history length.

Benchmark	Dep. Branches	Min Hist Pos	Max Hist Pos
605.mcf_s	43	2	1,221
620.omnetpp_s	188	3	801
623.xalancbmk_s	176	1	1,879
625.x264_s	3	1	34
631.deepsjeng_s	484	1	878
641.leela_s	186	2	762
648.exchange2_s	167	1	863
657.xz_s	157	1	530

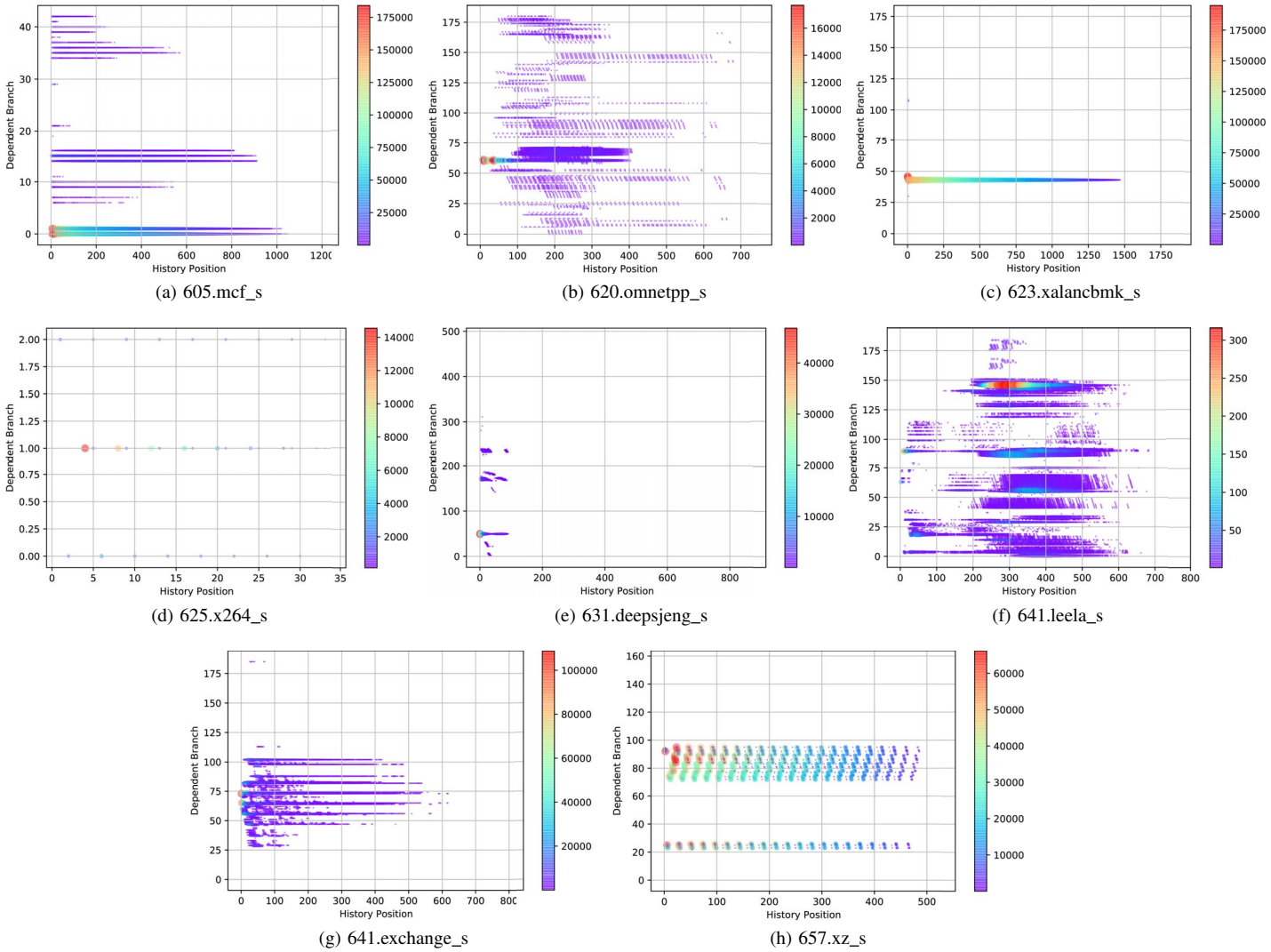
TABLE III: Summary of dependency branch statistics for the top H2P heavy hitter branch in SPECint 2017 benchmarks.

We directly measure the effect of this variation by tracking how TAGE-SC-L 64KB's table resources are allocated for H2P branches over time. TAGE-SC-L reserves entries for longer history lengths when the longest-matching sequence produces mispredictions, while marking incorrect or rarely used table entries for reallocation to other branches. Thus, H2P branches with high history sequence variation will result in abnormally high reallocation rates. Across our traces, we find that non-H2P branches are associated with a small number of allocations and that their entries are rarely reallocated—the median number of allocations per non-H2P branch is 4, while the median number of unique entries allocated to each is also 4. In contrast, H2P branches consume an outsized proportion of table entries, with few of these entries producing useful predictions. The median number of allocations per H2P is 13,093, while the median number of unique table entries allocated to each H2P is only 3,990. The discrepancy between these numbers is due to entries being allocated, then scrapped for use by another branch, and eventually being allocated for the same H2P branch once again. On average, we find that each non-H2P branch individually accounts for less than 0.01% of allocations, whereas each H2P branch accounts for 3.6%. *This behavior shows that TAGE-SC-L's underlying pattern matching mechanism struggles to group predictive statistics in H2P history data, and that a large portion of storage resources are wasted as a result.*

B. Rare branches have poor statistics

Table II indicates that LCF applications have a large number of static branches that are only executed a handful of times. This suggests that the baseline 8KB storage for TAGE-SC-L may quickly fill with entries that are not reused.

In theory, simply increasing storage (i.e., increasing the table capacity) to accommodate more of these branches should proportionately improve IPC. We perform a limit study that incrementally increases total TAGE-SC-L storage from 8KB to 1024KB, as shown in Fig. 7. For each LCF application, we



(a) 605.mcf_s (b) 620.omnetpp_s (c) 623.xalancbmk_s

(d) 625.x264_s (e) 631.deepsjeng_s (f) 641.leela_s

(g) 641.exchange_s (h) 657.xz_s

Fig. 6: Distribution of the history position of dependency branches for example H2P heavy hitters in each of the SPECint 2017 benchmarks shown. The size and color of each data point is proportional to the occurrence of that dependency branch at the corresponding history position. Some data points are invisible because of low occurrence.

define the IPC opportunity as the IPC gap between TAGE-SC-L 8KB and perfect branch prediction. Then, at each storage size, we measure the portion of the IPC opportunity captured by TAGE-SC-L. We repeat this analysis for different CPU pipeline scales to extrapolate to future designs.

It is immediately apparent that even at 1x (Skylake) pipeline scale, TAGE-SC-L captures less than half of the IPC opportunity, even when afforded an impractically high 1024KB of storage. For almost all the measured LCF applications, the greatest IPC gain comes from increasing storage from 8KB to 64KB, after which improvements plateau. Worse yet, as the pipeline capacity is increased, scaling up storage yields dramatically diminished returns—at 32x pipeline scale, a maximum of only 34% of the IPC opportunity is captured.

We show that this lack of further improvement despite additional resources owes to the fact that there are insufficient opportunities to both learn and later reuse predictions for rare branches in LCF traces. In Section III-B, Fig 3 (middle) showed that, for LCF applications, 96% of static branches have fewer than 1,000 dynamic executions, 85% have fewer than 100, and that these rare branches have a wide spread in prediction accuracy (Fig. 4). Using the largest TAGE-SC-L 1024KB storage configuration, we simulate the impact of predicting all branches with more than 1,000 dynamic executions perfectly at 1x pipeline scale, and repeat this for all branches with more than 100 dynamic executions. These results are reported in Fig. 8, and show that, on average, 34.3% of the IPC opportunity in large code footprint application is due to rare branches (i.e., static branches with fewer than 1,000 dynamic executions) and 27.4% is due to the rarest branches (i.e., static branches with fewer than 100 dynamic executions). We observe that, *with such a large portion of IPC tied to branches with fewer than 100 dynamic executions over 30M*

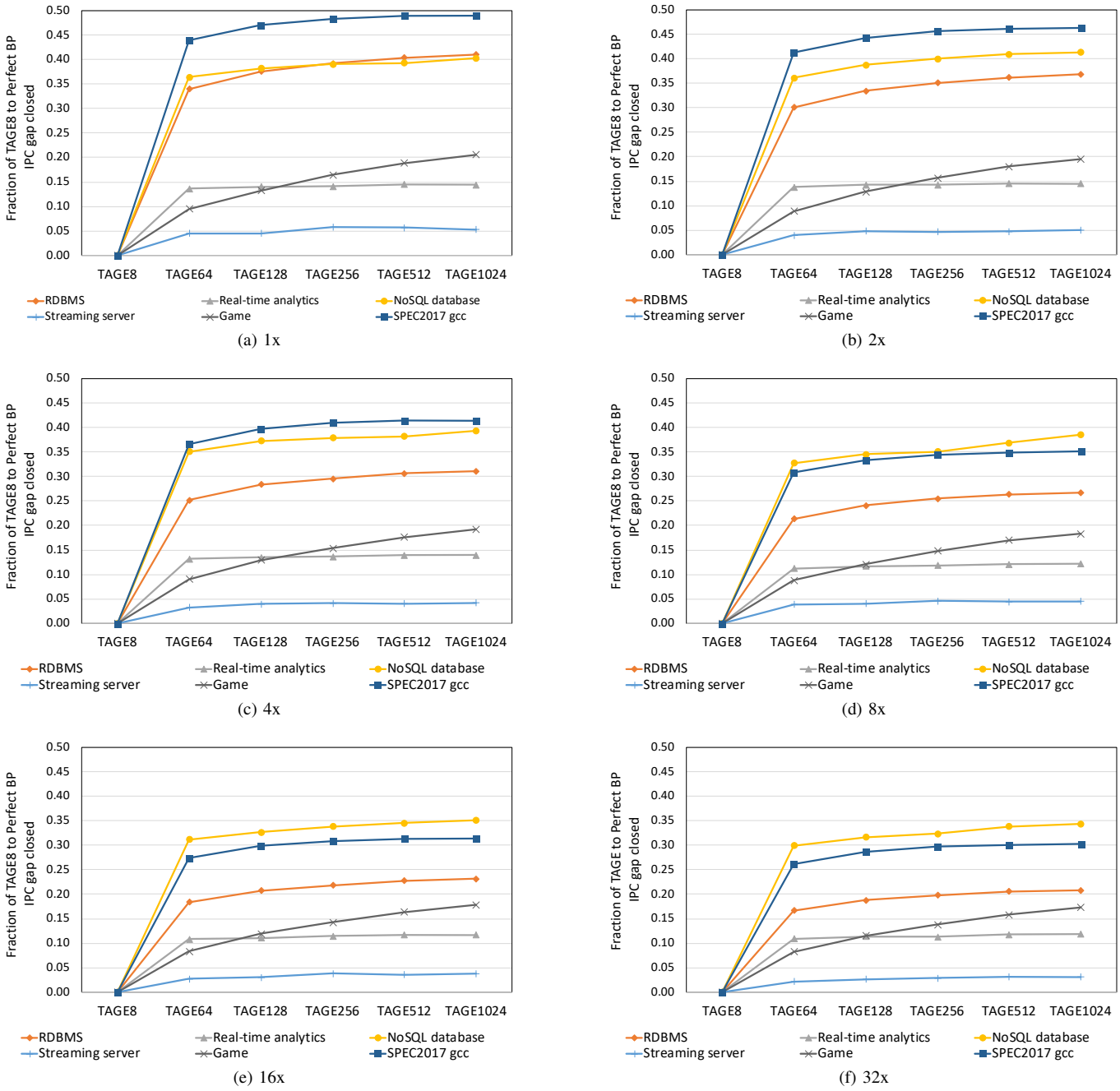


Fig. 7: Scaling up CPU pipeline together with the number of table entries for TAGE-SC-L has diminishing returns.

instructions, rare branches supply too few statistics to support stable learning and *later reuse at runtime.*

V. New Directions for Branch Prediction

The large IPC opportunity we have demonstrated and the inability of existing branch predictors to tap into it suggests that the time is ripe for reconsidering fundamental assumptions made in BPU design. Since TAGE-SC-L already does so well on the vast majority of branches, we argue that it should be left in place. Any additional resources given to the BPU should be devoted to augmenting it with other methods that directly address the challenges laid out in Section IV.

A. Reconsidering the deployment scenario

A key assumption in the design of branch predictors is the way in which they are deployed. This can be categorized based on whether branch statistics are captured, and the predictor is trained, *online* or *offline*; and, similarly whether predictions are generated (i.e., via inference) *online* or *offline*. Here, we define *online* as performing computations on the BPU and *offline* as employing computations that would require data, such as

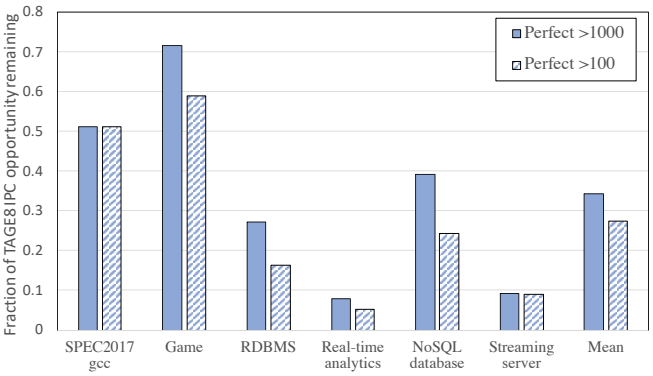


Fig. 8: The fraction of IPC opportunity remaining even after perfectly predicting all branches with more than 1,000 (solid blue) and 100 (striped) dynamic execution counts.

branch history or other microarchitectural state information, to be moved elsewhere.

Historically, branch predictors have assumed strict requirements that training and inference could only be performed online. However, this scenario limits the power of the algorithms available for pattern recognition, as well as their ability to exploit long-range statistical relationships. For example, the lightweight pattern recognition mechanisms found in perceptron predictors make a best-case assumption that pattern complexity is relatively low. Meanwhile, predictors such as TAGE-SC-L track statistics using low-bit width saturating counters that allow for just a small, fixed amount of hysteresis, and thereby make the implicit assumption that direction statistics are stable only in the short-term.

To successfully resolve the issues that existing branch predictors cannot, we argue that branch prediction techniques should not adhere solely to online-training/online-inference assumptions. By relaxing the constraints to allow for *offline training*, we open the door not only to training over a much richer set of data, but also to employing more powerful pattern recognition algorithms from machine learning.

B. Using richer training data

Branch predictors that solely perform online training are limited to the data available within the BPU as an application runs. Constraints on BPU storage capacity, e.g. due to layout, further impose an assumption that recent program state is the best predictive signal of a branch outcome. This ignores the possibility of contributions coming from distant program states, such as prior executions of the same SimPoint phase, or even statistics derived from prior application executions. Furthermore, online branch predictors must be application-agnostic, or general enough to perform universally well for all applications.

Offline training (for online prediction), however, has no such limitations. In particular, we argue that the key advantage to offline training is the ability to train predictors from a much larger set of statistics specific to a target application, for example aggregated over multiple executions. Successful offline training would thus rest upon *collecting multiple long-duration traces of an application, executing over multiple distinct application inputs*, as in the trace collection methodology we employed above. We note that this differs markedly from the relatively short single-input traces employed in CBP challenges, and corresponds to a large shift in the basic assumptions of current branch predictor development.

For H2P branches, where long history lengths are useful for capturing predictive signals in dependency branch correlations (recall Fig. 6 in Section IV-A) but are also the source of high history variation, offline training supports the ability to identify ground-truth predictors such as dependency branches. One actionable way to exploit analyses similar to ours is to design filters for a BPU to reduce data variation when predicting H2Ps. This would reduce the difficulty of on-BPU learning and make more efficient use of limited on-BPU storage when folded into existing algorithms such as TAGE-SC-L.

Offline training provides an additional method to address LCF applications that we found to be capacity limited, i.e. those that saw performance gains when TAGE-SC-L storage grew from 8KB to 64KB. This is because, under storage pressure at 8KB, TAGE must "forget" predictive patterns to make room for new ones. Identifying and storing predictive signatures that are stable over the long term would reduce the burden on TAGE to repeatedly relearn the same predictions.

Offline training is particularly useful for the many pockets of code in LCF traces that execute infrequently over a single invocation of an application. At the extreme, whenever an application is launched, TAGE learns from scratch, no matter how many times the application had been invoked in the past. This leaves on the table a significant opportunity for model reuse and iterative refinement. Recording statistics over multiple invocations of the same application—and over distinct application inputs—increases the number and variation in the samples of rare branches found in these pockets. As a result, offline training can yield more stable, higher confidence predictive signatures for the rare branches that plague LCF traces than online methods.

Beyond generating a rich trace library, it is also possible to incorporate data other than branch histories, from sources outside the BPU. One example is program phase information. Program phases are a well-known phenomenon [19] and can exist on different time scales. These can be inferred to a degree from the recurrence interval of dynamic branches (i.e., the number of instructions between two consecutive dynamic executions of the same static branch IP). For instance, if a branch has a very short recurrence interval, then it may be part of a tight loop. Conversely, a very large recurrence interval may be indicative of a much more macro-level program phase, spanning perhaps hundreds of thousands or even millions of basic blocks. Fig. 9 shows the distribution of the median recurrence interval of static branch IPs in the LCF dataset. In aggregate, the applications in this dataset have median recurrence intervals peaking between 100,000 and 1,000,000 instructions (ignoring the singleton branches in the first bin), suggesting that phases of sufficient and varied sizes are

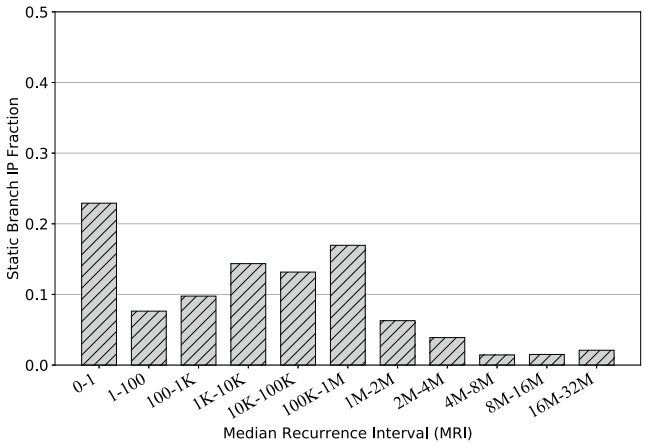


Fig. 9: The distribution of the median recurrence interval of branches in the LCF dataset. The recurrence interval is defined as the number of instructions between two consecutive dynamic executions of the same static branch IP. The distribution indicates that phase-like behaviors on relatively long timescales exist in the LCF dataset, and that these phases can be exploited as an additional input signal to helper predictors.

available to exploit. Phase information can be derived from architectural counter values over time, as in recent works [22], [23]. Conditioning branch histories on such phase information serves as another way to improve training by reducing the variation in the branch history data.

Yet another example of off-BPU information that could easily be incorporated into offline training are the register values immediately preceding a dynamic branch. For data-dependent branches, which typically resist prediction when using global branch histories alone, this could be an additional correlative input signal to boost prediction accuracy. In Fig. 10, we plot the distribution of the register values (lower 32-bits) written to each of 18 tracked registers, immediately preceding the dynamic executions of the top H2P heavy-hitter in each of the SPECint 2017 benchmarks shown. Two observations can be made readily: (1) that one distribution is drastically different from the next, indicating that we should focus on training branch-specific predictors; and (2) that there is complex but recognizable structure in the distributions, suggesting that more sophisticated machine learning algorithms such as neural networks may be useful for extracting the underlying patterns.

C. Using machine learning models

By removing the requirement of online training, we also effectively remove all computational constraints from the training process. Whereas online training methods are limited to the storage and operation complexity available on-BPU, training offline, e.g., over the above trace datasets, can take advantage of the virtually unlimited compute and storage resources of cloud computing infrastructures. This admits the use of powerful machine learning algorithms such as convolutional neural networks (CNNs), which can more fully extract patterns from the high-volume, high-complexity, and high-variation H2P and rare branch data. We refer to powerful predictors specialized to individual branches as *helper predictors* since they are intended to be deployed alongside an existing baseline predictor such as TAGE-SC-L. In our companion paper on CNN helper predictors [7], we show that *models trained offline on applications traced over multiple inputs can generalize to unseen inputs*, thereby significantly improving online prediction accuracy upon deployment.

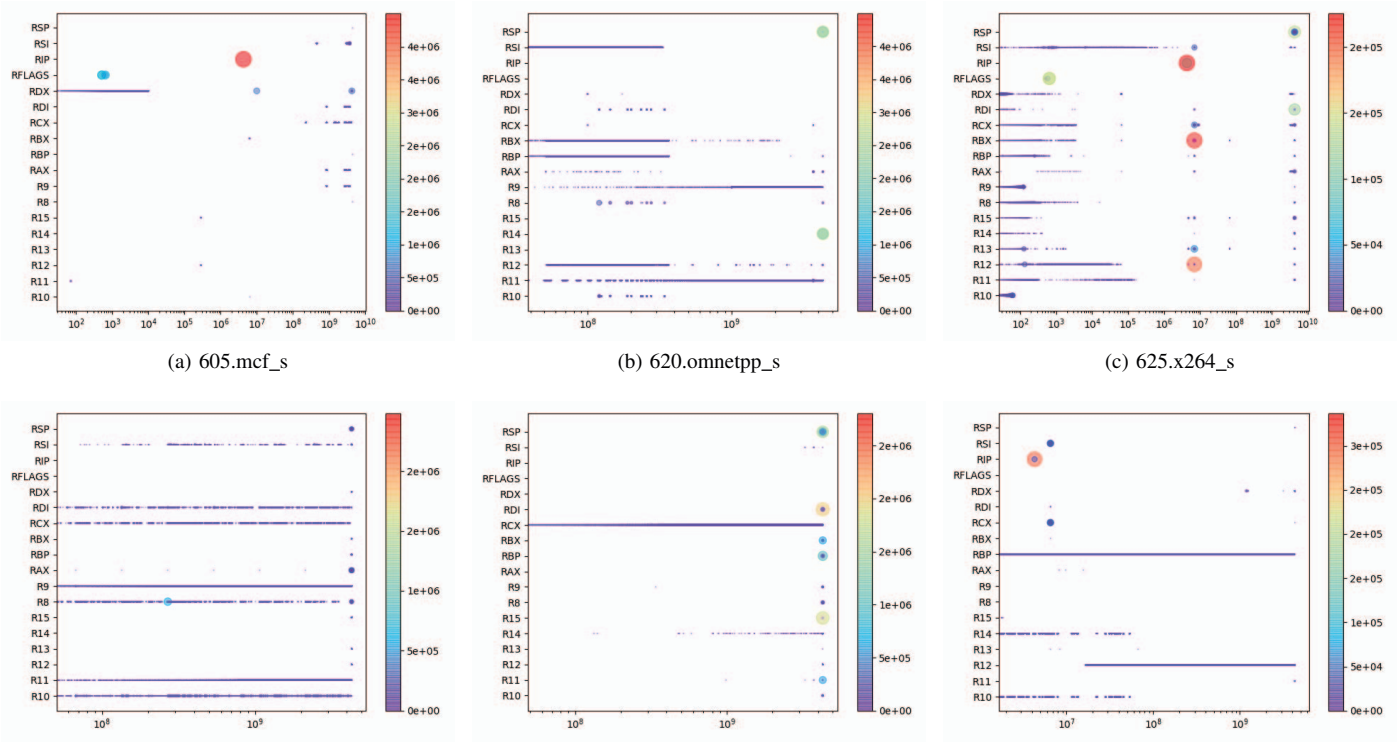
Of course, performing inference online using models that were trained offline can still be computationally expensive, but other works [22], [24], [7] have shown that it is indeed feasible to implement even sophisticated machine learning inference algorithms within current area and latency constraints. In the case of our CNN helper predictors, we take advantage of low-precision (2-bit) neural networks [25] and a custom input encoding method to simplify the forward pass (inference) computation to require just a handful of bitwise operations.

D. Amortizing offline training costs

One key issue that offline-training/online-inference predictors face is whether the high cost of collecting comprehensive training data and of offline training is worth the effort and resources. We argue that such an approach is particularly well-suited to data center applications, where performance is of paramount importance and where the training costs can be amortized through economies of scale. Under this framework, a customer's critical data center application would first be instrumented and then traced. Subsequently, helper predictors would be trained offline on the collected traces. Once trained, the predictors' model parameters (e.g., network weights in the case of a CNN) could be stored as application metadata, e.g., under a new segment type in an ELF binary. The new application binary would be installed on machines across the data center, where each machine's OS would manage loading the predictor(s) onto the BPU. This ensures that gains in prediction accuracy can be applied at scale. Once this infrastructure is in place, it then becomes possible to periodically update models with additional training data. In this way, helper predictors can be iteratively refined over time, a key advantage over existing online BPU mechanisms. Of course, the exact mechanics of this deployment model is the subject of future work, but we note that it is consistent with other runtime hardware optimizations in the recent literature [26], [27], [24], [22].

VI. Conclusions

In this paper, we characterized branch mispredictions under the state-of-the-art TAGE-SC-L branch predictor. Using SPECint 2017 benchmarks and a set of large code footprint applications, we demonstrate that there remains an untapped IPC opportunity due to these mispredictions, the size of which is on par with advancing process technology. We identified hard-to-predict (H2P) and rare branches as two classes of branches whose mispredictions account for this missed IPC opportunity, and showed that simply scaling up the storage capacity of TAGE-SC-L global history tables does not rescue these mispredictions.



(a) 605.mcf_s (b) 620.omnetpp_s (c) 625.x264_s

(d) 631.deepsjeng_s (e) 641.leela_s (f) 657.xz_s

Fig. 10: Distribution of register values written immediately preceding the top H2P heavy hitter branch in each of the SPECint2017 benchmarks. We record the bottom 32-bits of register writes in 18 tracked registers. The x-axis plots the actual register value and is log scale. Each data point represents a register and a written value; its size and color is proportional to the number of times the value was written to the register.

From these measurements and analyses, it is clear that branch prediction is far from being solved and that there remains substantial headroom for BPU improvement. In response, we propose new assumptions for branch predictor development—namely, *offline training* on data aggregated over multiple application executions. This approach enables new research directions that directly address the causes of mispredictions for both H2P branches and rare branches. These include exploiting more diverse training data to improve statistical power for rare branches, as well as additional computational resources to train specialized helper predictors for specific branches.

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