# Threshold-BasedMarkovPrefetchers

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#### Abstract

In this report we present a novel technique for a M arkov prefetcher designed to hide memory latency. This pr efetcher makes use of the information about previous cache misses in a memory trace and effectively predicts f uture misses with high accuracy and cover agerate. The an alysis of the memory traces of the executed benchmarks rev eals that our threshold-based prefetcher poses an optimi zed memory bandwidth overhead while not hurting the pre *fetcher coverage and effectively increasing its acc* uracy. Our data indicate that the average loss in coverage is1% while the gain in accuracy is 13% and the reduction in memory bandwidth overhead is 39%. The design also achieves more than an order of magnitude reduction in mispredictions as compared to previous results.

# Keywords

HidingMemoryLatency,MarkovTables

# BACKGROUND

As modern superscalar processors get higher clock s and deeper pipelines the cost of memory latency bec an increasing burden on the system performance. Pre ers are a mechanism that aims to hide the memory la inmodern processors by fetching data from memory b the processor actually requests it. The data is typ fetched following a model pre-established by the sy designer and itisstored indedicated buffers. peeds omes fetchtency ically stem

Several researchers have worked on different models fora prefetcher design, including compiler-dependant pre fetchers, strideprefetchers, streambuffers and correla tion-based prefetchers. Joseph and Grunwald studied Markov pre fetchers as a model for correlation prefetchers [1] .Intheir work, they considered and simulated the above prefe tchers inadditiontoaMarkovmodel.Theyfoundthatthe Markov prefetcher provided the best performance for the SP **EC95** applications that we reconsidered. Nonetheless, the vrecognized the need to reduce the bandwidth usage and th epossibilitytoimprovetheprefetcheraccuracy.

The main idea behind utilizing a Markov table in a prefetcheristoaccountfortheprobabilitiesoftran sitionsfrom one state to another state. In this context, a stat erefers to a certain miss address following a given miss address . The frequencies of transition are used to populate a ta ble as shown in table 1, and these frequencies are utilize d as a measure of probability for the prediction of future transitions from a reached state. The table is continuous updated and a stride prefetcher is also used in ord hance the performance of benchmarks that exhibit a stridedaccesses. lot of

Table 1: A Markov table populated by the transition	s and
frequency of transition occurrence for the sequence	of states
(cachemisses):A,B,C,D,C,E,A,B,C	

MissAddress (currentstate)	NextMiss(state)			
Α	B[2]			
В	C[1]			
С	D[1]	E[1]		
D	C[1]			
E	A[1]			

# **HYPOTHESIS**

In[1], the authors implemented a Markov design bas edon themissoccurrences of the L1-Cache; they built a Markov tree based on the next reported misses (states) of a given miss.Infacttheywouldalwaystrackandprefetch nextfour states of a miss. We propose to create and simulate amore dynamic model that adapts to the frequency of occur rence of next states. The prefetcher would only prefetch among the tracked next states theses misses that exceeded in the past a given threshold of appearance. In our opinio n, prefetching misses based on past frequency of occurren ceusing our dynamic threshold would improve prefetcher accuracyandreducethememorybandwidth.

Oursolutionassumesthattheprobabilityofoccurr<br/>missiscorrelated to the history of occurrence of<br/>Inother words, if "miss B" occurred after "miss A"<br/>time in the past then it has a 50% chance of occurr<br/>and thus is useful to prefetch.ence of a<br/>that miss.<br/>half the<br/>ing now

To confirm our assumption we examined the data-L1 m iss stream of several SPEC2000 benchmarks and found goo d evidence to our intuition. Figure 1 shows a sample of the behavior that proves the viability of our hypothesi s. In the VPR benchmark, the frequency of occurrence of misse s grows as the program progresses, i.e. the misses th peared in the past are likely to appear in the futu relative frequency of occurrence is more likely to stantor changes lowly throughout the program's lif ethanto change behavior drastically.



Figure 1: VPR samplenext misses from L1 miss strea mshows the number of occurrences of "next-miss" at progres sive time periods of the program.

Т8

Т9

T10

□ 1001C4D0

Τ6

Τ7

Early examination of the miss stream confirmed seve ral The observations from previously published results [1]. mostnotableisthatsomebenchmarks-likemcf-wil lbenefit little from a Markov prefetcher alone; as most of their cache misses exhibit a strided access behavior and not a correlation between previous history and the curren t time instances. The abundance of the strided access thus overwhelmsthenumberofmissesthatcanbenefitfroma correlation prefetcher. For that reason we decided to pl ace a stride prefetcher in series and ahead of the Markov prefetcher.

Inthisreport, we did not consider timeliness and we did not run any timing simulations on the data. On the othe rhand we gauge memory bandwidth usage by looking at then umber of memory references initiated by the Markov pr fetcher. In addition, having implemented the Markov prefetcherfollowing as trideprefetcher we will measu recoverage and accuracy for the Markov independently.

In this paper we will use the same terminology esta blished in[1]toevaluateour prefetcher, namely we will use the two following metrics:

• The coverage defined as the fraction of memory references that were supplied by the Markov prefetcher

and not demand-fetched or supplied by the stride pr e-fetcher.

$$Coverage = \frac{hits in prefetch buffer}{total cache misses}$$

• AccuracyisdefinedasthefractionofMarkovprefe cachelinesthatwereactuallyusedbytheprocesso r.

Accuracy =  $\frac{\text{unique hits in prefetch buffer}}{\text{total prefetches}}$ 

The definition for accuracy has a main deviation fr omthe definition of the coverage in that it uses a differ ent metric for the number of hits in the prefetch buffer. In o urexperiments we found that a single prefetched entry in th e prefetch buffer may get used several times and this ca usedthe calculated accuracy to be above 100% and thus we mo dified the definition to account for the effect of mi spredictions which limits the accuracy to be always less t han 100%.

• The definition of misprediction used in [1] and the previous reports is given as the number of useless prefetches to the number of cache misses and this valu e canbein excess of 100%.

$$Misprediction = \frac{total prefetches - unique hits in prefetch buffer}{cache misses}$$

In our project we were analyzing the performance of the prefetcher on the memory accesses of the data strea similar arrangement can be implemented for the inst streamaswell.

# ARCHITECTURE

We assume a conventional modern architecture for th e cachestructureoftheprocessor.Wehaveseparate dataand instruction L1 cache; we will vary their size from 4 to 32 KB-andaunified1MBL2cache.Inaddition,wepla cetwo buffersatthesamelevelasL1.betweenL2andthe processor:thestrideprefetcherwhichholdsfourcachel inesof32 bytes each and the Markov prefetch buffer which hol ds32 lines of cache. These two additional buffers will b e dedicatedtodatamemoryreferencesonly.

Feedingthetwobufferswillbethestrideprefetch erandthe Markov prefetcher. The stride prefetcher looks for patterns ofstridedaccessestomemoryinthemissstreamo ftheL1, when such patterns are detected, a demand is placed tothe L2topassthedatatotheprefetcherthedatainto thestride buffer, such a demand would likely occur later when the memory reference actually misses in the L1 cache. I fno strided access is identified for a given miss, iti spassedto theMarkovprefetcher.TheMarkovtablewilluseth atentry to build the next state tree. If the miss follows a previously known miss it would be recorded as a next state or incrementthecorrespondingnextstateforthatpre-miss .Alsoif therecentmisshasatreeofnextstatesthatfoll owit,ademand for some or all of these next states will be p assedto L2.

In [1], the authors decided to always prefetch the next4 eonthe states, in our experiment we will dynamically decid number of states to prefetch. In fact we will keep track of the history of up to 16 next states but only fetch those whose frequency of occurrence has exceeded a given threshold. In this architecture, the prefetchers an dL1 compete for service from L2. The L1 requests are assum ed to always be given priority over the prefetcher reques ts because they are imminent and certain. The prefetchr equests are future and speculative as they are trying to gu ess an upcoming miss that may not occur. When the miss eve nts are spreadout in time, the prefetchers have a bett erchance ofbeingservicedbytheL2andofbeingeffective atgetting data from memory if needed in a timely matter. We h ave not considered the timeliness aspect in our paper a nd assume that the prefetcher shandle the predicted cachemisses sufficientlyaheadintimeoftheiractualoccurren ce.



Figure2:SystemDesign

Table2:Configurationpa	rametersforthesimulator
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	SizeKB				Rpl	A	lssoc.
L1-Cache- Data	4	8	16	32	LRU	d	irect
L1-Cache-Inst	4	8	16	32	LRU	d	irect
L2-Cache-Uni	1024			LRU	4	1-way	
TLB-Inst	256			LRU	4	1-way	
TLB-Data	512			LRU	4	1-way	

#### EXPERIMENTALMETHODOLOGY

For our simulations, we used SimpleScalar 3.0 to runn the followingSPEC2000benchmarks:mcf,equake,vpr,pand gzip. Since we were only interested in the cach emiss stream for the L1 data cache, we modified the file cache.c and recompiled simplescalar such that it would dump the data-L1 miss addresses. We then ran sim-cache on the benchmarks and redirected the output to a memory transformation and the simplescalar such that it would the simplescalar such that it would dump the benchmarks and redirected the output to a memory transformation and the simplescalar such that it would the simplescalar such tha

file. In running the benchmarks, we used input data sets provided in the ELEC525 class directory on owlnet; the SPEC 2000 REDUCED folder. We stopped the simulations when we have collected information in excess of 6Megabyteswhichisroughlyequivalenttothefirst 500000 L1datacachemissesthatoccurredinthebenchmark WeransimulationsfordifferentL1-cachesizes,4K B.8KB. 16KB and 32KB. Although we are only interested in t he data misses, both the data L1 and the instruction L 1 were modified to have the same size. On the other hand w edid not modify the size of the unified L2 cache for any ofthe runs. The complete parameter configuration that we used forsimplescalarislistedinTable2.

Wethenused the collected miss-stream information toanalyze the effectiveness of our dynamic prefetcher. T he prefetcher simulation code mimics the behavior of the cascaded Stride/Markov prefetcher described above. Par t of the code is responsible for collecting data about t he performance of the Stride and Markov prefetchers in or derto calculate the accuracy and coverage of each prefetc herand the performance of their combination for a given mi SS stream. The performance data is reported at the end ofthe simulation run. The following is an example of the output from analyzing 576853 d-L1 cache misses in the "equ ake" benchmark.

```
Number of L1 Cache Misses = 576853

STRIDE PREFETCH BUFFER

Number of Prefetches from L2 Cache = 70399

Number of Hits in Buffer = 63443

Number of Unique Hits in Buffer = 62756

Prefetch Coverage = 0.109981

Prefetch Accuracy = 0.891433

MARKOV PREFETCH BUFFER

Number of Prefetches from L2 Cache = 86

Number of Hits in Buffer = 291025

Number of Unique Hits in Buffer = 86

Prefetch Coverage = 0.504505

Prefetch Accuracy = 1.000000
```

Asmentionedearlier, thenumberofhitsisused to calculate the coverage and the numberof unique hitsisused to calculate the accuracy and misprediciton. In the examples to accuracy is 100%. This is due to the constraint heuristic used in controlling the prefect of the accuracy but indirectly gree pacted the coverage and the mispredictions. Calculate to calculate to calculate to calculate to accuracy and misprediciton. In the example accuracy is 100%. This is due to the constraint heuristic used in controlling the prefect of the accuracy but indirectly gree to the accur

The coverage is more than 50% and the misprediction is 0%! Such values are in huge contrast with the value s obtained in [1] and previous year ELEC525 reports. Th is is explained by the fact that the entries in the Marko v buffer were utilized more than one time and they did not g et evicted by unnecessary prefetches due to the constr will illustrate this inmore detail and with more b in the experimental analysis section of this report .

## **HWCOSTOFTHEEXPERIMENTALPREFETCHER**

The main blocks in this systemare the two prefetchbuffersand the two prefetchers. The following is a break down ofthe estimated hardware cost to implement each one ofthem.

The Markov prefetcher has the following configurati on parameters and associated hardware cost:

- 128 row entries. This is the number of miss addresses analyzed by the prefetcher.
- Upto16nextstatesperentry. (Weused4inour experiments)
- Counters to count the frequency of occurrence of eachnextstate.
- Comparators to detect if a counter has exceeded a preset threshold. The thresholds we used in our experiments are 3,5 and 10
- Eviction policy for the row and column entries of the table. In our simulation we used the least recently used (LRU) policy for both rows and columns. We intend in future work to consider random eviction and assess the performance vs. the reducedhardwarecomplexity.

TheMarkovPrefetchBuffer

- A32entryfullyassociativebuffer.
- UtilizestheLRUevictionpolicy

The Stride Prefetcher calculates the step in a stri ded memoryaccess and thus has the following cost

- Subtractor current miss address from a previous missaddresstogetcurrentstride
- Comparator to compare currently calculated stride to previously calculated stride and if they match it begins giving predicted requests to the L2 cache.

TheStridePrefetchBuffer

- Afourentryfullyassociativebuffer.
- UtilizestheLRUevictionpolicy.

The estimated storage requirement for the above HW configuration is 128KB. It is also assumed that it tak cycle to search the combined prefetch buffers on an miss.

#### **EXPERIMENTALANALYSIS**

In the following, we present our obtained results f ning the benchmarks with the different cache size c rations and with different threshold heuristic. The olds used in our experiments are 0, 3, 5 and 10. Th threshold is used to account for aggressive prefetc which does not make use of our heuristic. We use th at as a datum for evaluating the effect on performance when the thresholdheuristicisused.

Figure 3 illustrates the combined stride/Markov pre fetcher performanceintermsofaccuracy. The point of comp arison istheperformanceinconjunctionwiththethreshol dheuristic. The results for "mcf" are not affected becaus e"mcf" exhibits a large number of strided accesses and sin ce the stride prefetcher supersedes the Markov prefetcher. almost allthepredictionsbythestrideprefetcherwereu tilizedand the Markov prefetcher was prevented from carrying o ut unnecessary prefetches. This is further illustrated in Figure 4 and Figure 5 which show the prefetcher coverage d ueto each prefetcher. The Markov prefetcher almost didn otoperate at all in the case of the "mcf" benchmark. Fi gure 6 again compares the coverage obtained with an aggres sive zerothresholdMarkovprefetcherandwiththethres holdset at5.

The intuitive expectation is that the coverage would go up as the threshold is increased. The data in figure 6 indicate that the system with thresholds has max decrease of coverage of 12% and an average decrease of coverage of 12% the system with outprefetcher threshold.

Whilethishasbeenthetrendinallthecases, it is worthyto note the performance for cache sizes 4k and 8k in t he "equake" benchmark. The large increase in accuracy with the '5' thresholdMarkovprefetcheractuallyledto asubsequent improvement in coverage. The average increase in accuracy with the thresholdMarkovis13%

Infigures7and8, we compare the performance of t hesystemwiththeMarkovprefetcherthresholdsetat3, 5and10. The intuitive expectation that there will be an inc reasing trend for accuracy with threshold is not satisfied for all cache sizes. This result indicates that it is in ge neral requiredtodecidetheparametersoftheMarkovprefe tcherin conjunctionwiththecachesizesincethereisape rformance dependency. This observation requires further inve stigation inordertodetermineoptimumthresholdsvs.cache sizes.

In figure 9, we illustrate the percentage of reques tscarried out by the system which has a thresholded Markov pr efetcher normalized with respect to the prefetches o fasystem with unthresholded Markov prefetchers. In this case 100% represents similar usage to the system without threshold. The merit of evaluating this performance metric istoassesstheameliorationinmemorybandwidtho verhead imposed by the prefetcher. The maximum memory requ est decrease is 77% and the average request decrease is 39%. The results in general are in line with our propose d hypothesis.

The data we obtained for mispredictions are superiory or by orders of magnitude to that obtained in [1] and previous ELEC525 reports. This indicates that the inhibiting of the stride prefetcher over the Markov prefetcher has tremendously improved the Markov prefetcher performance metrics. In other words, the Markov prefetcher does not

operatewhenitisexpectedthatitwilldegradeth ance.AlsotheMarkovprefetcheroperationisdepen whetherthecachemississatisfiedbyeitherprefe Thisledtohavingthelargefavorablediscrepancy the number of hits in the prefetchbuffer and then unique hits. Although this was not intentionally de ourcode, it cameout as apleasant pug. eperformdenton tchbuffer. between umber of signedin

## CONCLUSIONSANDFUTUREWORK

In this report, we examined the construction of a p refetch buffer that hides memory latency and uses a Markov table for the prediction of the memory addresses for fetc hing. Theprefetcheroperationisbasedonathresholdhe uristicin order to increase its accuracy and reduce the memor у bandwidth overhead due to unnecessary mispredicted prefetches. While previous work has showed mispredicti onsin theorderof300%~600%,ourthreshold-basedMarkov prefetcher exhibited a misprediction penalty less than 10% in most of our test cases. The superior performance of our architecture is due in part to the accuracy of the strideprefetcher that we implemented. In our design, the Mar kov prefetcher is cascaded in series with the stride pr efetcher and the combined buffers are searched in parallel w henan L1 cache miss occurs. The threshold heuristic help ed improve the accuracy of the prefetcher with a slight 1% degradation in coverage. The resulting improvement in accuracyinsomecasesactuallyledtoimprovementinc overage. Theaverageincreaseinaccuracywasfoundtobe13 %.The

threshold heuristic also led to a decrease of memor ybandwidthrequirement of 39% on the average.

Thehardwarecostofthedesignisrelativelyhigh duetothe implementationoftheLRUpolicyinevictingrowan dcol-umnentriesintheMarkovtable.

For future work, we would like to experiment with o evictionpoliciesthatarelesshardwarecostlyand performance. A second suggestion for future work in the storage requirement of the data structures whic mated tobe 128KB. We think that the storage require should be in comparison with the size of the L1 cac thus more experiments need to be conducted in order abetter balance in storage requirements. the storage requirements.

We are also considering developing a functional har model using HDL that can be integrated with a proce core running on a prototyping platform. This model give an accurate identification of the HW cost and signtradeoffs.

# REFERENCES

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Figure3:CombinedPrefetcherAccuracywith'0'thr esholdintheMarkovprefetcher(gettingallexpect ed4nextentries)vs.gettingonlyentrieswhosecountercrossesthethresho ldsetat5













kovprefetcherthresholdssetat'0'and'5'





Figure8:CombinedprefetcherAccuracyfordifferen tMarkovprefetcherthresholdlevels



Figure9:PercentageofL2requestswithMarkovthr esholdsetat'5'ascomparedto100%beingthemem of Markovprefetcherthresholdis'0'.AlargerL1cac hesizemakesthenumberofL2requestslessanda cons centageofthoseisattributedtotheprefetcher.

oryrequestswhenthe consequentlyalargerper-