NC State University

Department of Electrical and Computer Engineering

ECE 463/563: Fall 2022 (Rotenberg)

Project #2: Branch Prediction

by

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NCSU Honor Pledge: "I have neither given nor received unauthorized aid on this project."

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Course number: 563

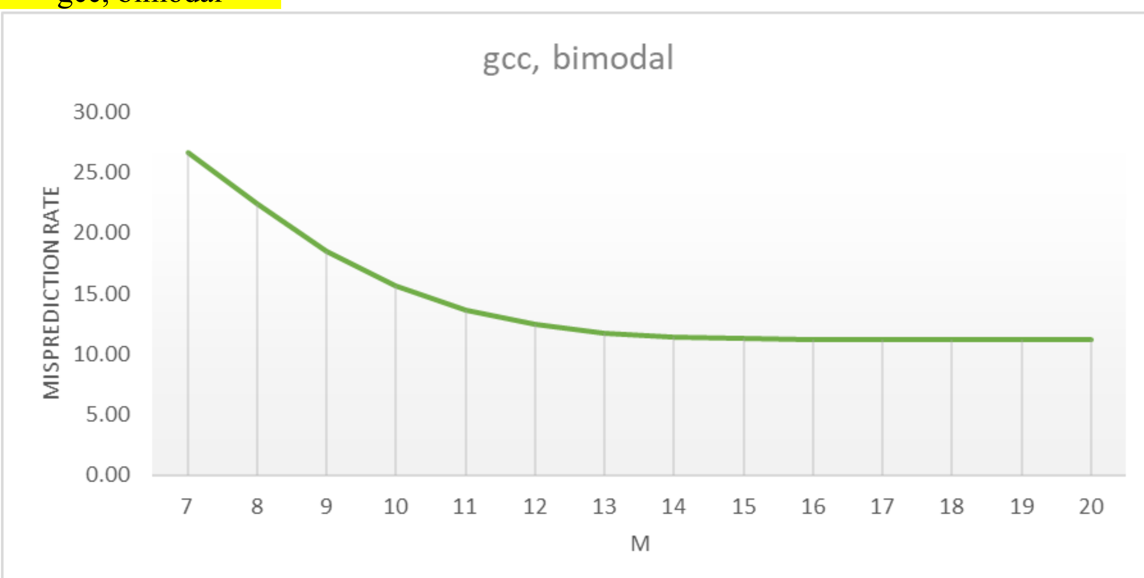
7. Tasks, Grading Breakdown

PART 1: BIMODAL PREDICTOR

(a) [**ECE463: 25 points**] or [**ECE563: 20 points]** Gradescope will evaluate your simulator on the four validation runs “val_bimodal_1.txt”, “val_bimodal_2.txt”, “val_bimodal_3.txt”, and “val_bimodal_4.txt”, posted on the website for the BIMODAL PREDICTOR. Gradescope will also evaluate your simulator on one bimodal predictor mystery run. Each validation run and mystery run is worth ⅕ of the points for this part (5 or 4 points each). Gradescope must say that you match all four validation runs to get credit for the experiments with the bimodal predictor, however.

(b) [**ECE463: 25 points**] or [**ECE563: 20 points**] Simulate BIMODAL PREDICTOR for different sizes ($7 \leq m \leq 20$). Use the traces ***gcc***, ***jpeg***, and ***perl***.
[20 or 15 points] Graphs: Produce one graph for each benchmark. Graph title: “<*benchmark*>, bimodal”. Y-axis: branch misprediction rate. X-axis: *m*. Per graph, there should be only one curve consisting of 14 datapoints (connect the datapoints with a line).

<< “gcc, bimodal” >>



<< “jpeg, bimodal” >>

<< “perl, bimodal” >>

[5 points] Analysis:

1. [1 point] As the bimodal predictor’s table size increases, the branch misprediction rate decreases and becomes constant_.

2. [2 points] For each benchmark, indicate the minimum value of *m* at which the misprediction rate bottoms-out (reaches its minimum) and indicate its minimum misprediction rate. Fill in the table below.

Benchmark	Minimum “*m*” at which misprediction rate reaches its minimum	Minimum misprediction rate
gcc	*m* = 18	11.17%
jpeg	*m* = 13	7.59%

perl	$m = 14$	8.83%

3. [1 point] At some point, increasing the bimodal predictor's table size is of no value. At this point, each static branch (*i.e.*, each static branch PC) is allocated a dedicated counter in the table. Given that interference among different static branches is eliminated at this point, the only way to improve accuracy further is a better prediction algorithm.

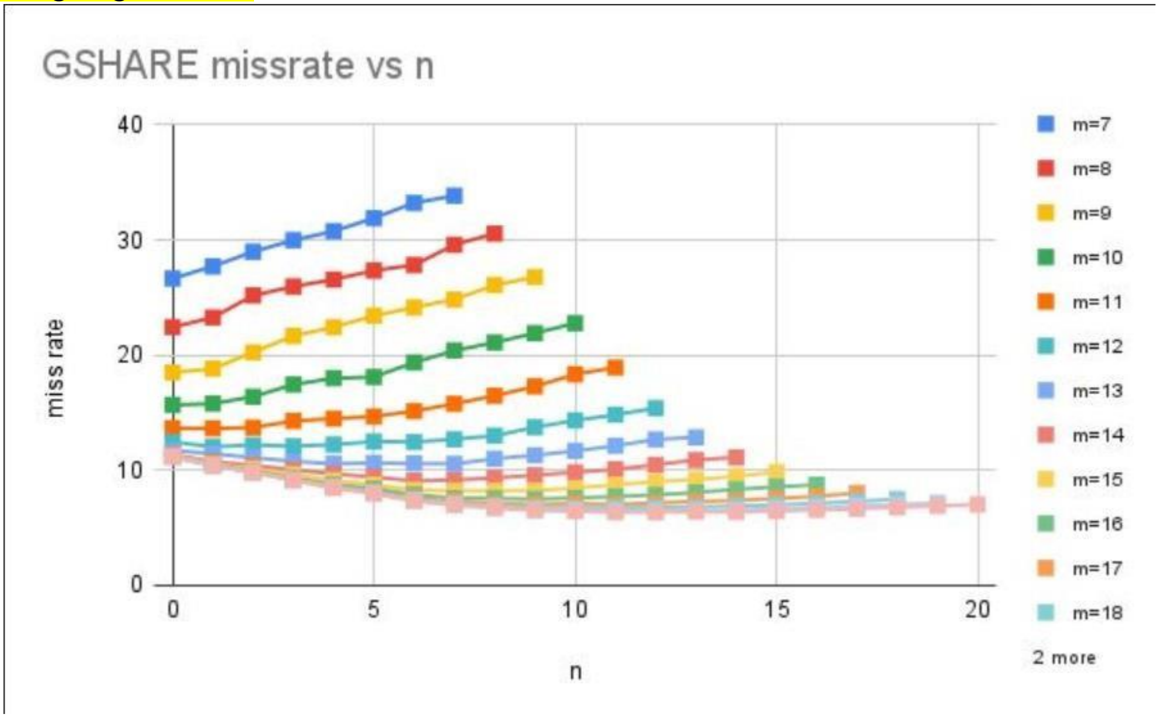
4. [1 point] I infer that ***gcc*** more has static branches (*i.e.*, unique static branch PCs) than ***jpeg***, because ***gcc*** more requires table entries than ***jpeg*** before its misprediction rate bottoms-out.

PART 2: GSHARE PREDICTOR

(a) [**ECE463: 25 points**] or [**ECE563: 20 points**] Gradescope will evaluate your simulator on the four validation runs "val_gshare_1.txt", "val_gshare_2.txt", "val_gshare_3.txt", and "val_gshare_4.txt", posted on the website for the GSHARE PREDICTOR. Gradescope will also evaluate your simulator on one gshare predictor mystery run. Each validation run and mystery run is worth ⅕ of the points for this part (5 or 4 points each). Gradescope must say that you match <u>all four validation runs</u> to get credit for the experiments with the gshare predictor, however.

(b) [**ECE463: 25 points**] or [**ECE563: 20 points**] Simulate GSHARE PREDICTOR for different sizes ($7 \leq m \leq 20$), and for each size, *i.e.*, for each value of *m*, sweep the global history length *n* from 0 to *m*. Use only the trace ***gcc***.
<u>[20 or 15 points] Graphs</u>: Produce one graph for ***gcc***. Graph title: "gcc, gshare". Yaxis: branch misprediction rate. X-axis: *n* (spanning *n*=0 to *n*=20). For this graph, there should be a total of 203 datapoints plotted as 14 curves. Datapoints having the same value of *m* (same predictor size) are connected with a line, *i.e.*, one curve for each value of *m*. Note that not all curves have the same number of datapoints; see the listing below for the number of datapoints for each of the 14 curves, *m*=7 through *m*=20. The rationale for this graph is to study the effect of global history length for each predictor size. m=7 curve has 8 datapoints: $0 \leq n \leq 7$ m=8 curve has 9 datapoints: $0 \leq n \leq 8$ m=9 curve has 10 datapoints: $0 \leq n \leq 9$ m=10 curve has 11 datapoints: $0 \leq n \leq 10$ m=11 curve has 12 datapoints: $0 \leq n \leq 11$ m=12 curve has 13 datapoints: $0 \leq n \leq 12$ m=13 curve has 14 datapoints: $0 \leq n \leq 13$ m=14 curve has 15 datapoints: $0 \leq n \leq 14$ m=15 curve has 16 datapoints: $0 \leq n \leq 15$ m=16 curve has 17 datapoints: $0 \leq n \leq 16$ m=17 curve has 18 datapoints: $0 \leq n \leq 17$ m=18 curve has 19 datapoints: $0 \leq n \leq 18$ m=19 curve has 20 datapoints: $0 \leq n \leq 19$ m=20 curve has 21 datapoints: $0 \leq n \leq 20$

<< “gcc, gshare” >>



[5 points] Analysis:

Insight: With the bimodal predictor (n=0: no global history), a given static branch is predicted using only a single 2-bit counter. With the addition of global history, that single counter is *specialized* or *multiplied* into many more counters. All these counters are used by the same static branch for more specialized predictions among its dynamic instances, promising higher accuracy *as long as there are adequate counters available in the table* (not just for this static branch, but for all static branches). Thus, with the addition of global history, there is a need for more 2-bit counters … the key idea being that, at some point, bimodal cannot even take advantage of more counters (see your analysis section for bimodal, above) whereas gshare *can*. Summarizing: *Gshare needs an abundance of counters and, unlike bimodal, it can exploit abundant counters for higher accuracy.*

1. [0.5 points] At small table sizes, global history can hurt accuracy. This is because there are abundant counters.
2. [0.5 points] At large table sizes, global history can help accuracy. This is because there are abundant counters.
3. [2.5 points] For each table size (*m*), indicate the global history length (*n*) that yields the lowest misprediction rate, indicate what that lowest misprediction rate is, and indicate the misprediction rate for bimodal. Fill in the table below.

m	Global history length (*n*) that yields the lowest misprediction rate	Lowest misprediction rate	Bimodal misprediction rate (*i.e.*, for *n*=0)
7	0	26.65	26.65
8	0	22.43	22.43

9	0	18.49	18.49
10	0	15.67	15.67
11	1	13.64	13.65
12	1	12.04	12.47
13	7	10.56	11.72
14	6	9.08	11.37
15	7	8.2	11.30
16	9	7.49	11.21
17	11	7.03	11.19
18	10	6.73	11.17
19	12	6.47	11.17
20	12	6.37	11.17

4. [0.5 points] The *smallest* bimodal predictor that achieves the best bimodal accuracy (lowest misprediction rate among all bimodal configurations) is as follows:

Best bimodal: *m* = 18, misp. rate = 11.17%.

5. [0.5 points] The *smallest* gshare predictor that achieves the best gshare accuracy (lowest misprediction rate among all gshare configurations) is as follows:

Best gshare: *m* = 20, *n* = 11, misp. rate = 6.37%.

6. [0.5 points] In conclusion, with adequate predictor storage budget, gshare rocks.

PART 3: HYBRID PREDICTOR (ECE563 students only)

[ECE563: 20 points] Gradescope will evaluate your simulator on the two validation runs "val_hybrid_1.txt" and "val_hybrid_2.txt" posted on the website for the HYBRID PREDICTOR. Gradescope will also evaluate your simulator on two hybrid predictor mystery runs. Each validation run and mystery run is worth ¼ of the points for this part (5 points each).