Exploring Perceptrons in Branch Prediction

February 28, 2002

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Branch Prediction

- CPU speeds are increasing
- Pipeline lengths are increasing
- What to do with a branch:
  - Stall? ☹
  - Predict?

    If correct: ☺

    If not: ☹ ☹ ☹

Better Branch Prediction

- Current branch predictors do really well:
  90+ percent accuracy
- How do they do it: Industry Secrets
- Is a 0.5% percent accuracy improvement really that helpful?

  100,000 branches

  $\Rightarrow$ 500 less pipeline flushes

  $\Rightarrow$ More throughput

But to quote Mark…

- “It’s all a HACK!”
- But it’s an interesting hack for *Machine Learning* due to the requirement of

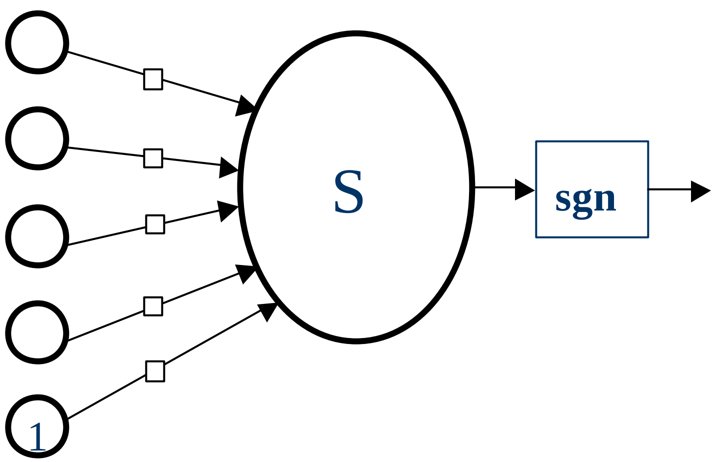
High Accuracy with Low Cost

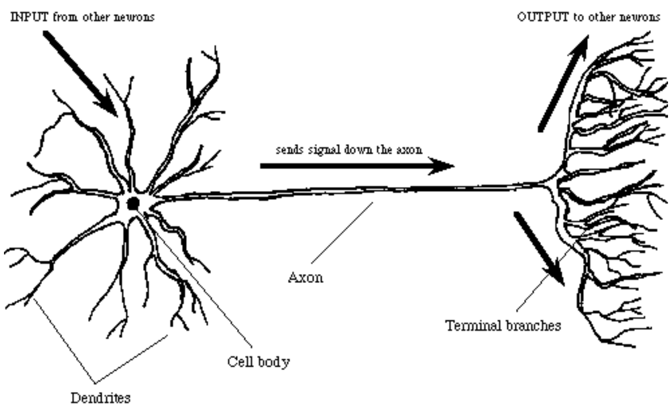
- Most machine learners can’t do this, except…

PERCEPTRONS

Perceptrons

- Simple model of a human neuron.
- Contains a weight vector ***w.***
- Takes a vector ***x*** of inputs.
- Outputs **sgn(*x*•*w*)**





Perceptrons

- So how do we get the weights?
  - Use Machine Learning!
  - Perceptron Training Rule:

$$w_i \leftarrow w_i + \Delta w_i$$

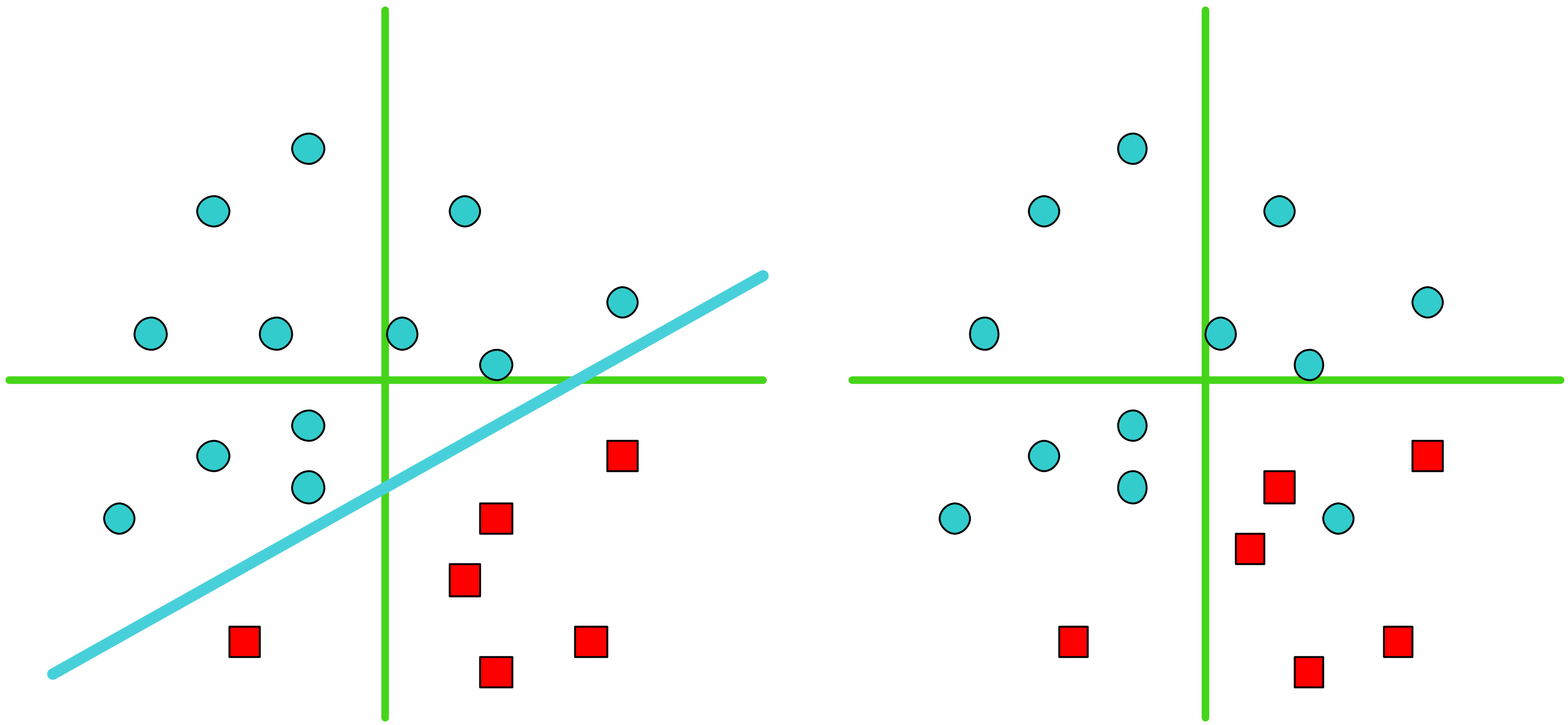
$$\Delta w_i = \eta(t - o)x_i$$

  - Guaranteed to converge to an optimal weight vector within finite time if:
    - We use a small ?.
    - The dataset is linearly separable.

Linear Separability

- Perceptrons can only learn functions of the form: $\mathbf{w_1x_1 + w_2x_2 + \ldots + w_{n-1}x_{n-1} + w_n = 0}$.
- Means that we must be able to divide classes of data using *n*-dimensional hyperplanes.
- Can still learn a lot of things:
  - AND, OR, NAND, NOR, NOT.

Linear Separability



Why use Perceptrons for Branch Prediction?

- Allows Dynamic Branch Prediction.
- Intrinsically robust to aliasing.
- Smaller hardware requirement than other AI techniques.
- Supply confidence values.
- Fast to train and predict.
  - Lots of multiplying by ±1 and adding
  - Lots of parallelism.

Previous Work: Jimenez & Lin, 2000

- First to adapt perceptrons to branch prediction.
- Simplified training rule: $w_i \leftarrow w_i + t \bullet x_i$
- Weight caps: $\Theta = \lfloor 1.93h + 14 \rfloor$
- Can't achieve 100% accuracy on linearly-inseparable branches.
  - Empirically, still do well on inseparable ones.
- Argue that prediction takes about 2 cycles on a 700MHz clock.

Previous Work: continued

- Jimenez and Lin also explored a gshare/perceptron hybrid predictor.
  - Generally outperformed gshare or perceptron alone.
- Found that some branches are best done with classical predictors.
- Michaud and Seznec (2001) found that using a few bits from the branch address improves linear-separability.

How to do Branch Prediction with Perceptrons

- Hash the branch address to get an index into a table of perceptrons.
- Fetch the appropriate perceptron.
- Compute the branch prediction.
- Act on the prediction.

- Train the given perceptron on the outcome.
- Write the trained perceptron back to table.

Previous Implementation Approaches

- Tracing of SPEC Benchmarks:
  - Run a benchmark
  - Record each branch and outcome to a file
  - Feed this file into a predictor simulator
  - Compare performances for different predictors
- Pros:
  - Faster than a CPU simulator
- Cons:
  - Ignores speculative predictions and garbage history

Speculative Predictions and Garbage History

X and Y are branches. X is predicted taken.

Global History = 1001

X $\xrightarrow{\text{40 cycles}}$?

Y $\xrightarrow{\text{10 cycles}}$ NO

X's Outcome	Global History	Correct History
YES	0 1 0 1	0 1 1 0
NO	0 1 0 0	0 0 1 0

How to Deal with Speculation

- How do they do it in real processors?
  - They don't. It's too costly to fix.
- Doesn't that affect how the predictor learns?
  - Yes, but these "errors" are consistent with its behavior.

Our Implementation

- Add a perceptron branch predictor to sim-alpha using the same design as the Jimenez paper
- Basic Configuration:
  - # of perceptrons
  - Size of the global history
  - Size of the local history
  - Threshold value on the weights
  - One input to every perceptron is always set to 1

A Bit about History Bits

- Global History:
  - A record of the last *n* branches (1 = taken)
  - Shared by all perceptrons
  - Updated speculatively
- Local History:
  - IDEAL: A record of the last *m* branches for a particular address
  - REALITY: A record of the last *m* branches for a particular perceptron
  - Update speculatively

A Bit More about History Bits

- Gshare: After history length exceeds 10 bits, performance degrades
- Perceptrons: Performance increases with longer histories
- The Jimenez paper's magic formula:

$$\theta = \lfloor 1.93h + 14 \rfloor$$

Hardware Tradeoffs

- Gshare and other predictors use a small amount of hardware: (usually 1024 2-bit SUD counters)
- Each perceptron must store its weights and its local history
- Compensation:
  - Keep the local history relatively small compared to the global history
  - Use less perceptrons

Benchmark Testing

- Currently using these SPEC2000 benchmarks:
  - CINT: vpr, gcc, parser, twolf
  - CFP: lucas
- Due to time concerns, using only the *test* inputs instead of the *ref* inputs

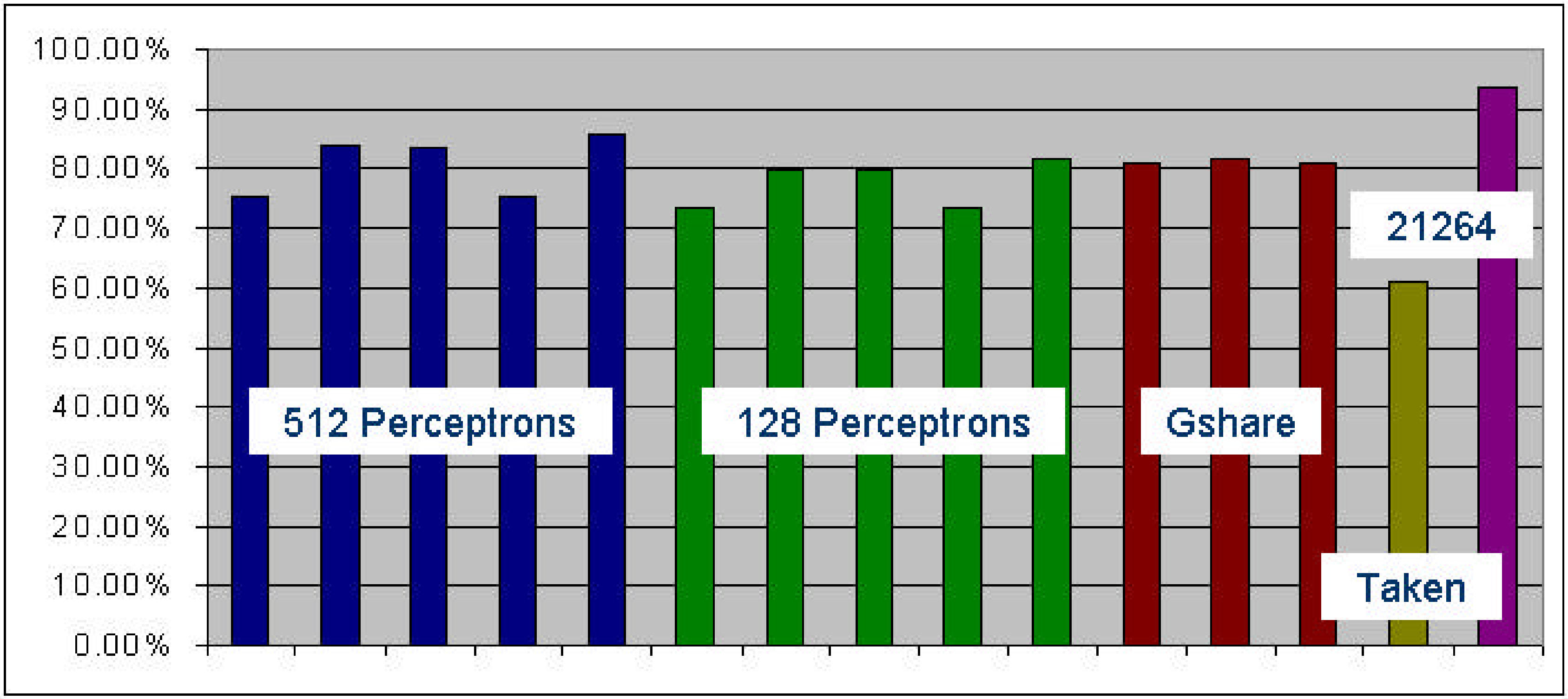
Our Experimental Method

- Compare the perceptron predictor's performance to other predictors:
  - Always Taken Predictor
  - Gshare:
    - 1024 counters
    - Global history length: 8, 10, 16
  - 21264 Predictor:
    - Sim-alpha's guess of how the 21264 really works

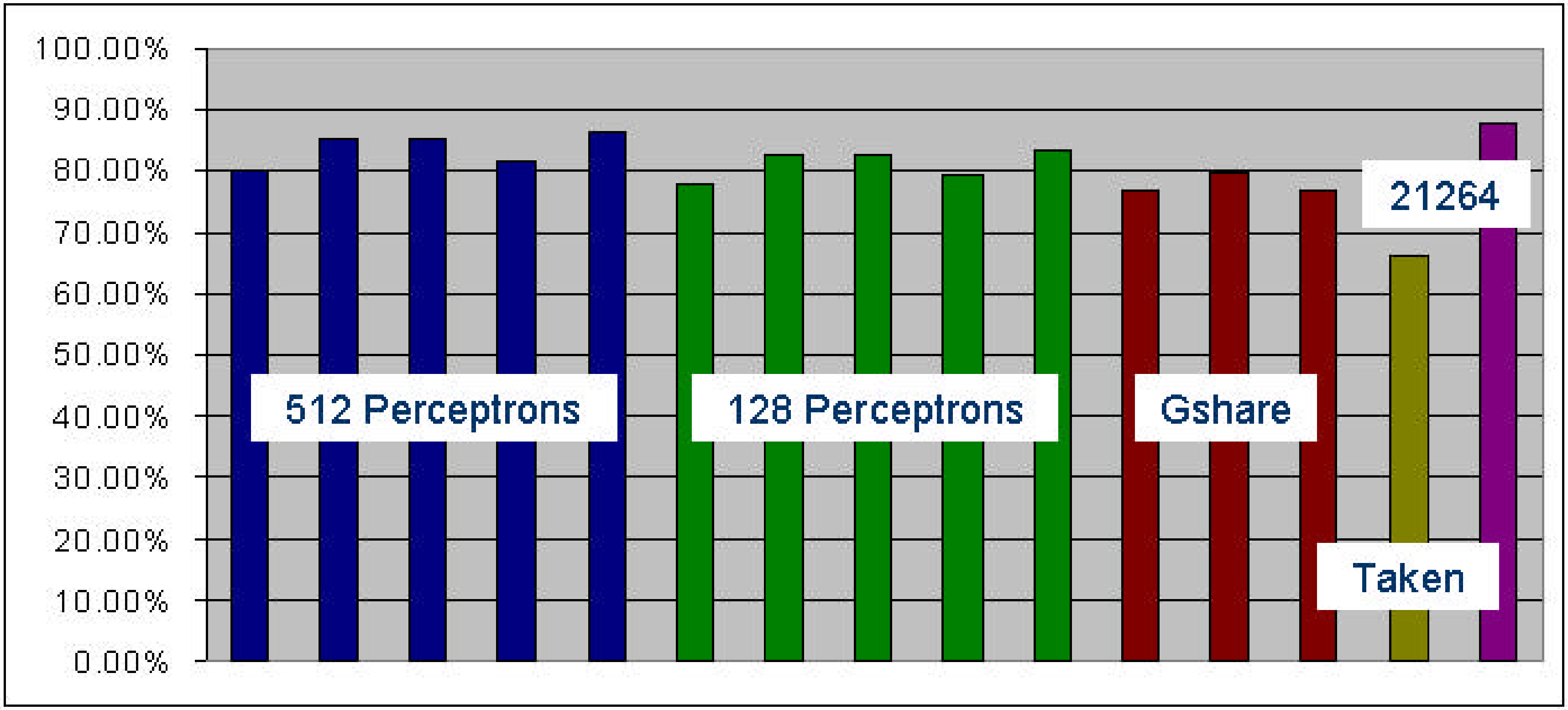
Perceptron Configurations

- # of Perceptrons: 512 vs 128
- Local History Size: 0, 5, and 10 bits
- Global History Size: 20 and 25 bits
- Threshold: with and without the magic formula

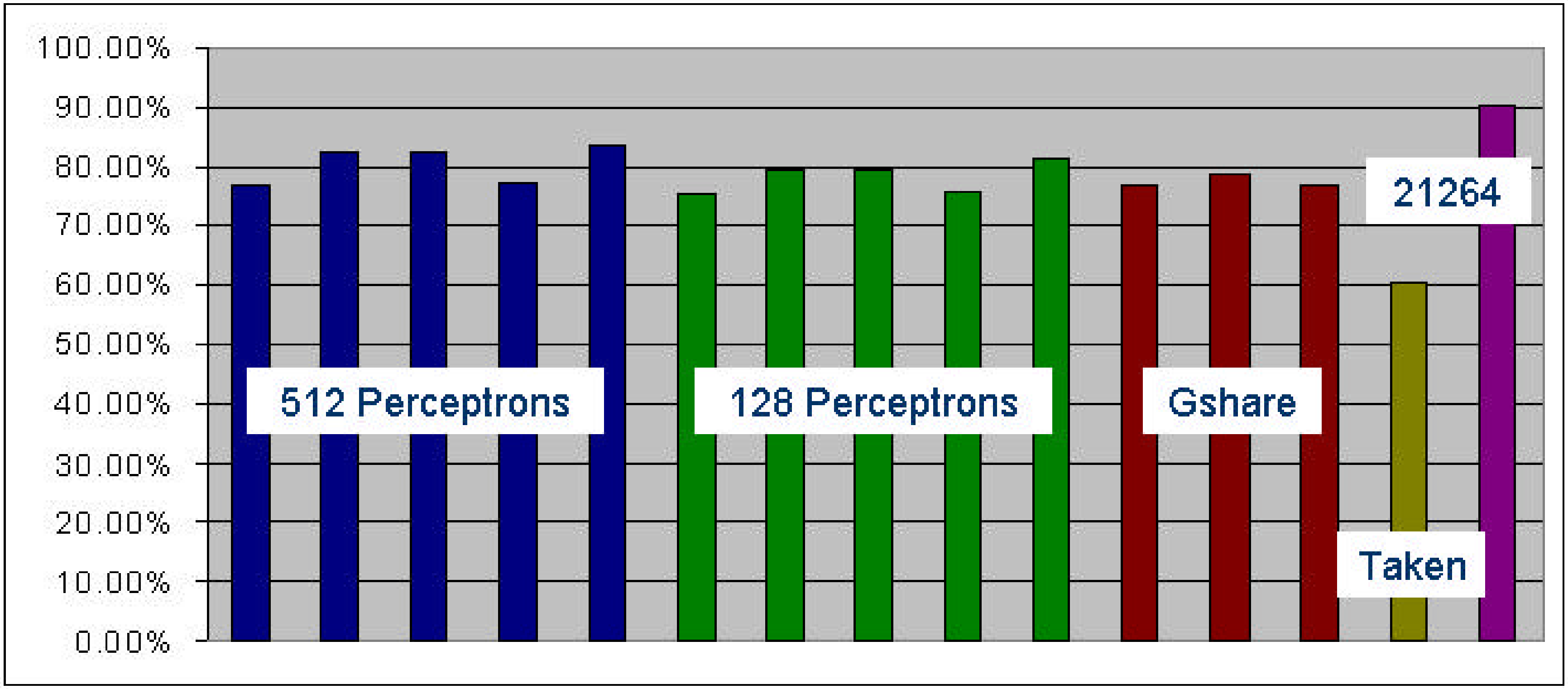
GCC Benchmark



VPR Benchmark



TWOLF Benchmark



An Up Close Look at the Data

GCC Benchmark				
Predictor	**Direction Hits**	**Direction Misses**	**Total**	**Percentage Predicted**
Perceptron: 512,0,20,52	238195317	79164520	317359837	75.06%
Perceptron: 512,5,20,52	265314537	52053250	317367787	83.60%
Perceptron: 512,5,20,62	265157819	52207845	317365664	83.55%
Perceptron: 512,0,25,62	238519623	78841970	317361593	75.16%
Perceptron: 512,10,20,81	272613439	44760254	317373693	85.90%
Perceptron:128,0,20,52	232351139	85012059	317363198	73.21%
Perceptron: 128,5,20,52	253213011	64152929	317365940	79.79%
Perceptron: 12,5,20,62	253003396	64363919	317367315	79.72%
Perceptron: 128,0,25,62	232594537	84767405	317361942	73.29%
Perceptron: 128,10,20,81	258691841	58677654	317369495	81.51%
Gshare: 1,1024,10,1	256427183	60948583	317375766	80.80%
Gshare: 1,1024,8,1	259465549	57910011	317375560	81.75%
Gshare: 1,1024,16,1	256427183	60948583	317375766	80.80%
Always Taken	193367708	123988295	317356003	60.93%
21264	295950630	21422272	317372902	93.25%

Local History Makes A Difference

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The Magic Formula Flops

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Gshare and History Size

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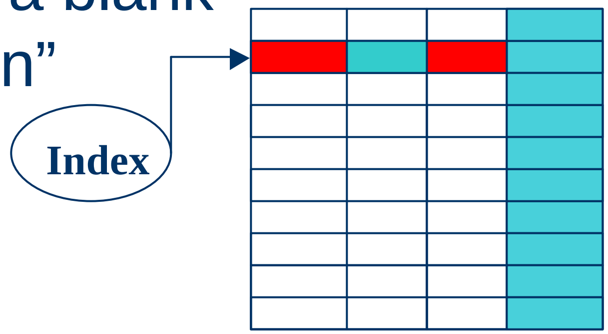
Set-Associative Perceptron Tables

- Usually, we use a hash to index into a table of perceptrons.
  - This is exactly like indexing into a direct-mapped cache.
- Try applying 4-way set associativity to perceptron tables.

Set-Associative Perceptron Tables

- It is not immediately clear if associativity will be effective:
  - Set-Associativity is a tool for avoiding aliasing.
  - Perceptrons are already robust to aliasing.
  - Is there a better way to spend hardware budget?
  - What to do on a replace? Load a blank perceptron? Maintain a “common” perceptron? Do nothing?
  - Victim caching? L2 Cache?



Learning Rule Enhancements

- Imagine a human training a perceptron by hand - what would the human do?

  Perceptron Mispredicted: Decrement the Weight.

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- Human would cheat - If perceptron is *way* off, decrement by a larger number.
- Hopefully, this would speed convergence.

Learning Rule Enhancements: First Approach

First Approach:

- Employ a Saturating Counter.
- Set to zero on a correct prediction, increment on a misprediction.
- When we are saturated and mispredict, adjust weight by 2 instead of by 1.

Learning Rule Enhancements: Second Approach

- See how far off the perceptron is in predicting the outcome.
- If we are VERY far off, adjust weight by 2 instead of 1.

$$\left\| (w \bullet x) - w_n \right\| >> n$$

Learning Rule Enhancements: Risks

- Increased chance of oscillation.
- Increased hardware complexity.
- Good if we are in a tight loop. Bad if we aren't.

Immediate Plans

- Implement and collect data on:
  - Set-associative predictor
    - With or without the common perceptron
    - With or without the victim cache
  - All designs with the advanced learning rule
- Determine what specific data to collect:
  - Dependence on # of perceptrons
  - Proper threshold values when using local history
  - Good sizes for the victim cache

And some future plans…

- Add all of our perceptron predictors as a configurable option in sim-alpha
- Potentially investigate:
  - Hybridizing our predictors with gshare
  - Using perceptrons as part of a tournament predictor like the Alpha 21264 predictor
  - The performance of a perceptron predictor in a multithreaded environment

And the Oracle says…