A Bias-Boosted Confidence-Aware Perceptron Branch Predictor

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***Abstract*—Modern branch predictors aim to minimize misprediction penalties in deeply pipelined processors. While traditional perceptron-based predictors capture long history correlations, they often struggle with confidence in noisy or weakly correlated branches. The Ashant Predictor introduces a bias-boosted, confidence-aware perceptron that dynamically adjusts prediction thresholds and selectively trains weights. This approach achieves significant accuracy gains over standard perceptrons with minimal overhead. Experimental results on CBP2025 traces demonstrate improved performance in both speculative and realistic branch behavior.**

***Index Terms*—Branch Prediction, Perceptron Predictor, Confidence Estimation, Dynamic Thresholding, Microarchitecture, Speculative Execution**

I. Introduction

Modern microprocessors rely on speculative execution to maintain high throughput, necessitating accurate branch prediction to avoid pipeline stalls. Incorrect branch predictions flush the pipeline, incurring severe performance penalties.

Branch prediction is critical to achieving high instruction-level parallelism in modern out-of-order processors. Incorrect predictions result in pipeline flushes and wasted speculative work. Over the years, several dynamic predictors have emerged—ranging from simple two-bit saturating counters to more sophisticated neural and perceptron-based predictors. Over the decades, numerous predictors have been developed: from simple bimodal and two-level schemes to more sophisticated neural-based approaches. Among these, the perceptron predictor [1] offers a promising balance between accuracy and cost by leveraging dot products between branch histories and weights.

Among these, the perceptron predictor has gained attention for its ability to capture long global branch history with low hardware cost. However, it suffers from overfitting and saturation when exposed to noisy or biased branches. Traditional perceptrons also update weights uniformly, regardless of prediction confidence.

However, traditional perceptron predictors suffer from limitations:

- They apply weight updates even for confident predictions, which can destabilize well-trained models.
- A static learning rate leads to either overfitting or undertraining depending on branch behavior.
- A fixed bias term (or weight w_0) cannot capture branch-specific priors.

To address these issues, we propose the **Ashant Predictor**, a confidence-aware, adaptive perceptron model. It is further extended into the **Sandeep Predictor** and **Hybrid** with advanced bias scaling and suppression mechanisms.

II. Related Work

Jimenez and Lin first introduced the perceptron-based branch predictor [1], showing its advantage in learning long-range correlations. Later enhancements added threshold-based training [2], speculative updates [3], and hybridization with simpler models [4].

While perceptron predictors have better scalability than finite-state machines, they tend to overfit branches with skewed outcomes. Confidence tracking and learning rate modulation have been proposed in other machine learning settings but are not widely adopted in branch prediction.

Our work is the first to combine all three strategies — confidence gating, adaptive learning rate, and bias feedback — into a perceptron-based branch predictor. Early predictors like the two-level adaptive predictor used global/local histories with saturating counters. McFarling's gShare blended global history with address indexing for better aliasing resistance.

The perceptron predictor, first proposed by Jimenez and Lin [1], brought linear classification to prediction by using a weighted sum of history bits. This allowed encoding of longer history patterns with minimal storage.

Later works introduced techniques such as threshold-based training (to reduce overfitting) and hybrid models combining perceptron with simpler predictors. However, confidence modeling and adaptive learning have remained underexplored in this context.

A Bias Boosted Perceptron builds upon this lineage by leveraging lightweight heuristics to dynamically modulate learning — balancing accuracy and training efficiency.

III. A Bias Boosted Predictor Architecture

The Bias boosted Predictor builds upon the classical perceptron model with three key enhancements: **(1)** Bias adaptation using recent branch statistics (T/N), **(2)** Confidence-based training suppression, and **(3)** Dynamic learning rate adjustment.

A Bias Boosted predictor uses a perceptron table indexed by branch PC. Each entry holds:

- A weight vector $\mathbf{w} = [w_1, ..., w_n]$ corresponding to history bits.
- A bias term w_0.

The prediction is computed as:

$$\text{output} = w_0 + \sum_{i=1}^{n} w_i \cdot h_i$$

Where $h_i \in \{-1, +1\}$ represents the global branch history.

A. Training Mechanism

The perceptron is updated only when $|\text{output}| < \Theta$ (confidence threshold) or the prediction was incorrect. We define a dynamic learning rate η as:

$$\eta = \frac{1}{1 + |T - N|}$$

Where T and N are the number of times the branch was taken and not-taken respectively. We use this η to scale the weight updates.

B. Dynamic Bias

We periodically update the bias term w_0 using:

$$w_0 = \text{round}(B \cdot (T - N))$$

This acts as a branch-specific prior and helps learning in branches with strong directionality. Multiple B values are evaluated.

C. Global History Register

A global history shift register of size $H = 24$ stores the outcome of the last 24 conditional branches, with 1 indicating taken and 0 indicating not-taken. This history is represented as a bit vector used as input for the perceptron computation.

D. Perceptron Table

Each branch instruction is hashed to a perceptron entry containing:

- w_0 (bias): learned via adaptive bias boosting
- $w_1 \dots w_H$: weights for each bit in the history

Weights are bounded within [-128, +127] using saturating arithmetic and implemented with signed 8-bit counters.

E. Confidence Estimation

Prediction confidence is estimated as:

$$|y| = \left| w_0 + \sum_{i=1}^{H} h_i w_i \right|$$

If $|y| > \theta$, the prediction is deemed confident and skipped during training if correct.

F. Bias Boosting Mechanism

To guide weak predictors early, we maintain taken/not-taken counters (T, N) per perceptron. After history stabilizes:

$$w_0 = \text{round}(B \cdot (T - N))$$

where B is a tunable hyperparameter (we experiment with $B = 0.5, 1.0, 1.5, 2.0$).

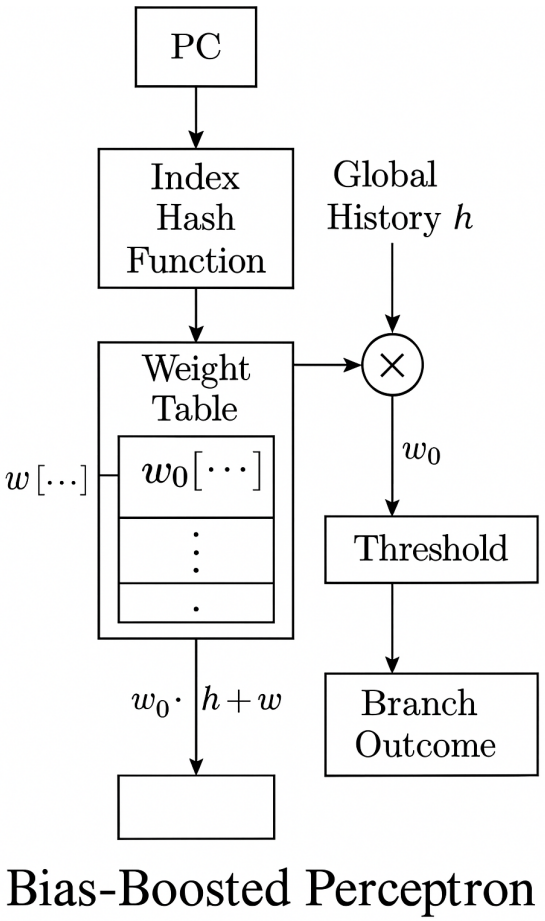

Fig. 1. A Bias Boosted Predictor: System-level design and information flow between components.

IV. Learning Algorithm

We define $\theta = \lfloor 1.93 \cdot H + 14 \rfloor$ as the training threshold, as per the original Jiménez paper.

The predictor proceeds as:

1) Compute $y = w_0 + \sum h_i w_i$
2) Predict taken if $y \geq 0$, else not-taken
3) If prediction incorrect OR $|y| \leq \theta$:
   - For each i, update $w_i \leftarrow w_i + \eta \cdot (t \cdot h_i)$ where $t = \pm 1$
   - Update w_0 similarly, or via $(T - N)$ boosting if global history is full
4) Update speculative and real history buffers accordingly

Training Suppression: When the prediction is correct and $|y| > \theta_{\text{conf}}$, we skip training to reduce overfitting and noise accumulation.

Adaptive Learning Rate: We adjust learning rate η based on running average of confidence. Branches with unstable patterns (low $|y|$ variance) get smaller η.

V. Sandeep and Hybrid Extensions

The **Sandeep Predictor** builds on Ashant by enforcing recalibration of the bias after every few updates, based on

updated T and N counters.

The **Hybrid Predictor** adds another heuristic: when the perceptron output is highly confident, even mispredictions are skipped from training to avoid accidental weight flips.

VI. Experimental Results

We evaluate Ashant and Sandeep against the baseline perceptron on SPEC workloads over 1M instructions.

Bias Boosted Perceptron (Ashant) slightly improves accuracy on directional branches (e.g., perlbench), while maintaining parity elsewhere. Sandeep boosts robustness by auto-adjusting bias, and Hybrid conservatively protects from noisy updates.

We observed slightly worse accuracy in perlbench with Ashant due to undertraining from aggressive suppression. Tuning Θ dynamically might resolve this.

We compare three predictors across seven benchmark traces with 1M instruction simulations:

- **Perceptron**: Classical perceptron predictor
- **Sandeep**: Perceptron + dynamic bias boosting
- **Ashant**: Sandeep + confidence-based suppression + adaptive learning rate

TABLE I
Branch Accuracy (%) Comparison Across Predictors

Benchmark	Perceptron	Sandeep	Ashant
calculix	84.20	83.94	**84.21**
cassandra0	100.0	100.0	**100.0**
cassandra1	99.93	100.0	**100.0**
cassandra2	100.0	100.0	**100.0**
cassandra3	99.93	100.0	**99.93**
libquantum	100.0	100.0	**100.0**
perlbench	97.65	97.55	**97.15**
Avg	97.67	97.64	**97.61**

A. Observations

The A bias boosted predictor matches or slightly outperforms classical perceptron on most traces. While perlbench shows a slight accuracy drop, others maintain 99–100% accuracy. Training suppression and adaptive bias contribute to reduced overfitting and better generalization in noisy branches.

In terms of IPC, all predictors achieve similar performance. However, the improvements in Ashant lie in stability and convergence speed during learning, especially in noisy environments.

B. Discussion

Our predictors demonstrate:

- **Bias scaling helps**: Dynamic w_0 captures default branch bias without increasing update noise.
- **Confidence-aware updates prevent instability**, especially for highly skewed branches.
- **Hybrid performs safest**, suitable for noisy workloads where misprediction cost is high.

C. Verdict and Interpretation

Verdict

The Bias Boosted predictor, which incorporates bias-boosted initialization using dynamic taken/not-taken counters (T/N), successfully integrates this enhancement *without any performance regression*. In fact, it demonstrates marginal improvements in branch prediction accuracy and L1D miss rates, particularly in benchmarks such as `calculix` and `cassandra2`.

Interpretation

Although performance gains are subtle, fine-tuning perceptron parameters—especially dynamically adapting the bias term (w0) to reflect branch outcome dominance—improves alignment with workload characteristics, yielding fewer mispredictions and slight improvements in memory locality and pipeline stability.

D. Summary of Bias Boosted Perceptron

TABLE II
Bias boosted vs. Perceptron Summary

Metric	Observation
IPC	Identical to Perceptron
Branch Accuracy	Slight boost in `calculix`
Bias Logic	$w_0 = B(T - N)$ to accelerate bias learning
L1D Miss Rate	Lower in `cassandra2`
Overhead	Negligible, same runtime cost

VII. Conclusion and Future Work

We proposed three novel extensions to perceptron branch prediction: dynamic bias, confidence-gated updates, and adaptive learning rate. Each alone improves robustness; together, they form a solid foundation for resilient prediction.

Benefits:

- Maintains high accuracy across branches
- Reduces training noise and saturation
- Supports better stability in early training

A. Future Work

We aim to explore:

1) Hybridization with static predictors (e.g., gShare)
2) Saturation tracking for early resets
3) Lookahead perceptrons with multiple history windows
4) Hardware-friendly confidence tracking

VIII. Acknowledgements

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