DistriHD: A Memory Efficient Distributed Binary Hyperdimensional Computing Architecture for Image Classification

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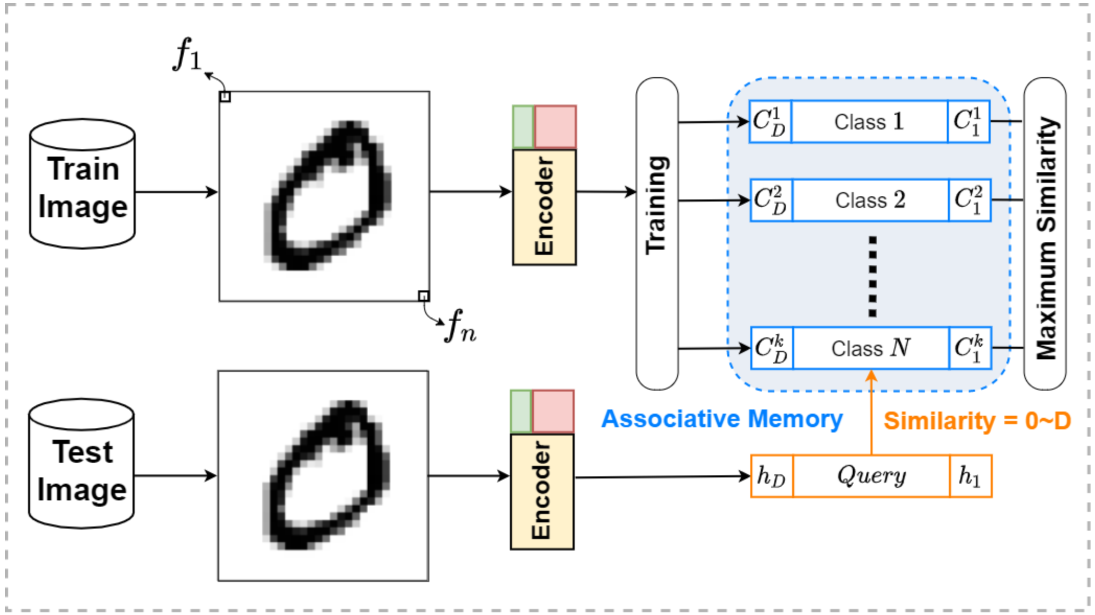
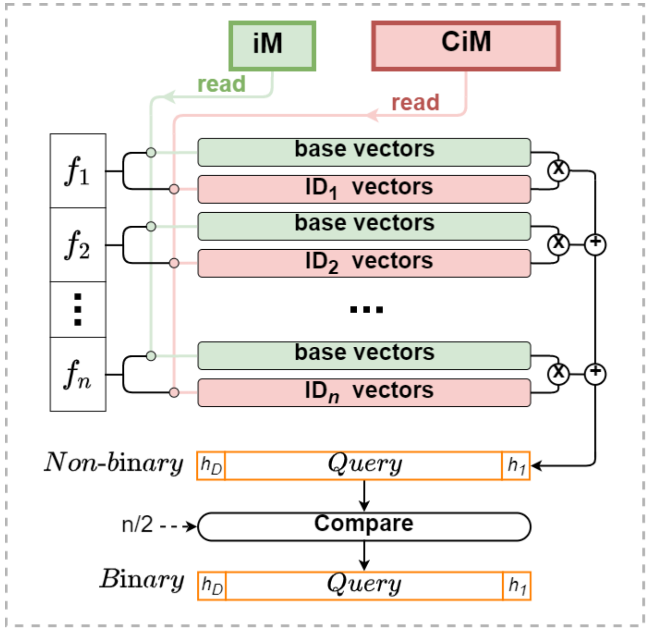
Outline

Background of Hyperdimensional Computing

- Demand for a more processing efficient model.
- Hyperdimensional (HD) Computing is a promising alternative method.
    - ✓Fast learning process.
    - ✓High robustness.
    - ✓Hardware friendly and light-weight.



Overview of General HD



General Encoding

Challenges and Contributions

- **Challenges in Previous Work:**
  - Use non-binarized hypervectors → High computational cost & memory requirement.
  - Retrain the model with iterative learning method → Tens of training iterations.
  - Compress the model base on dimension-wise sparsity → Feature-wise sparsity.
- **Main Contributions in *DistriHD*:**
  - **High memory efficiency**

    Support **binary** hypervectors and eliminate the costly CiM & iM.
  - **Fast Training**

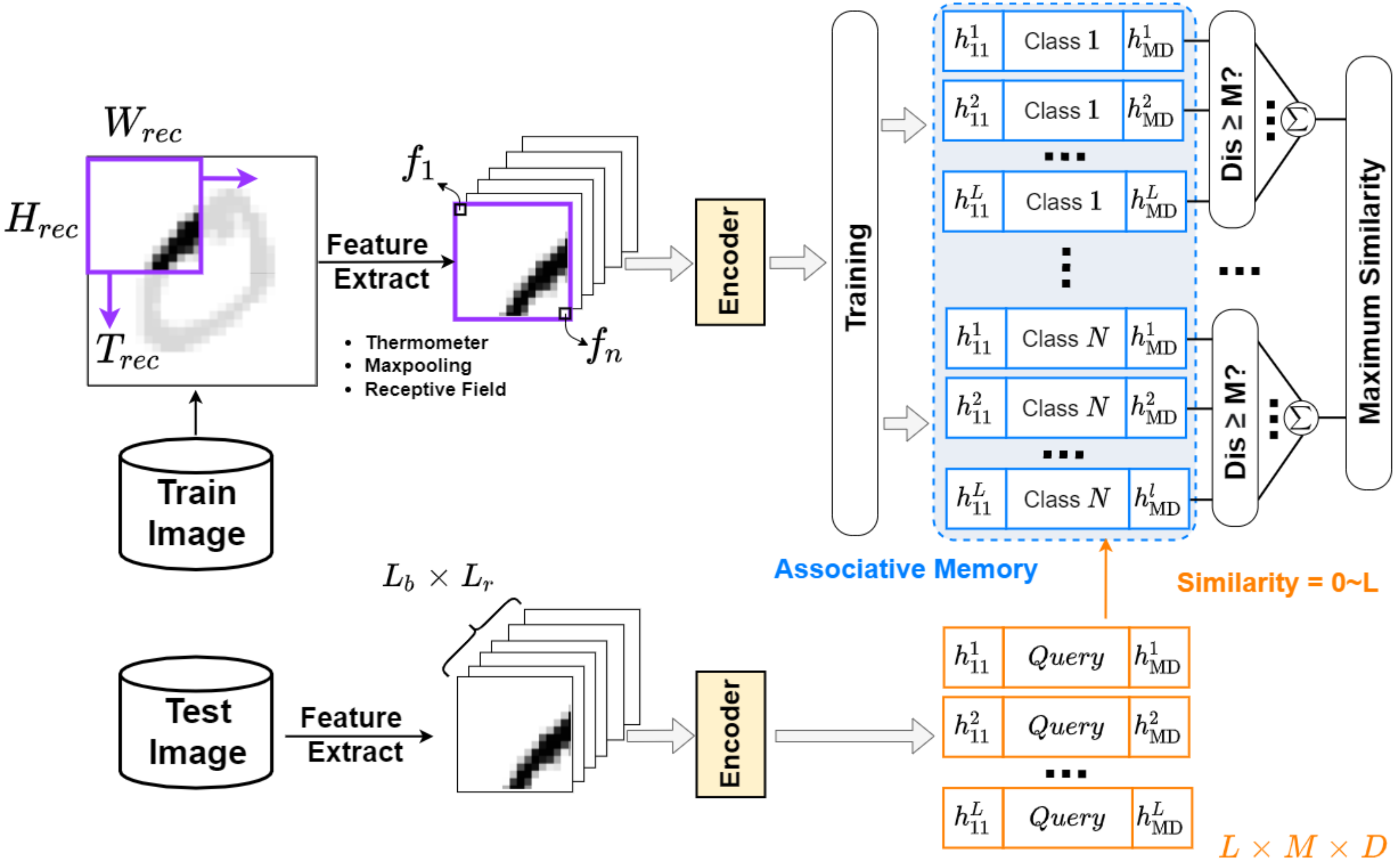
    Training process can be accomplished in **single-pass** way, while the baseline work [1] requires tens of iterations to retrain the model.
  - **Hardware friendly**

    27.6x reduction in inference memory cost without hurting the accuracy.

    9.9x and **28.8x** reduction in area and power, respectively.

[1] M. Imani et al., "A Binary Learning Framework for Hyperdimensional Computing," in DATE, 2019.

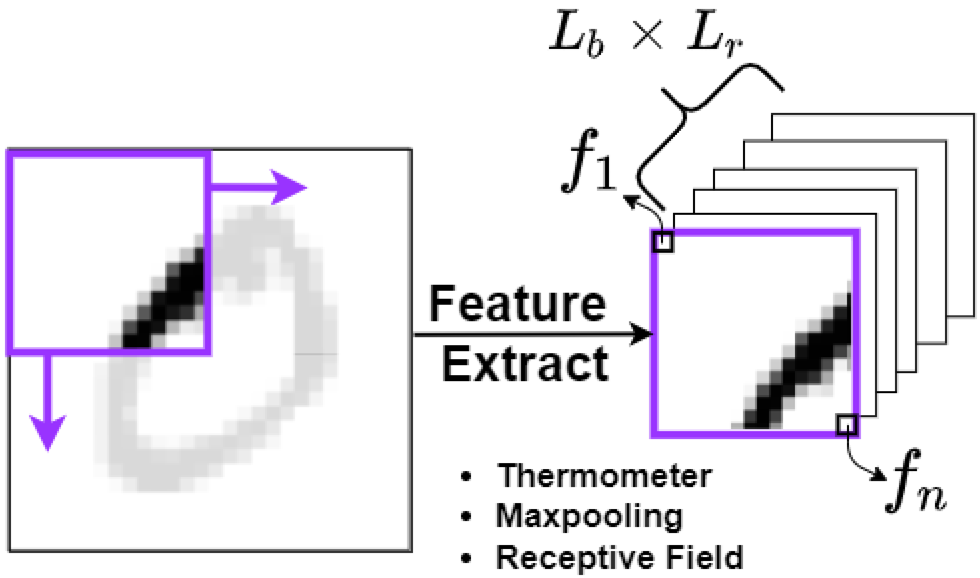
Proposed Method — Overview of *DistriHD* Architecture



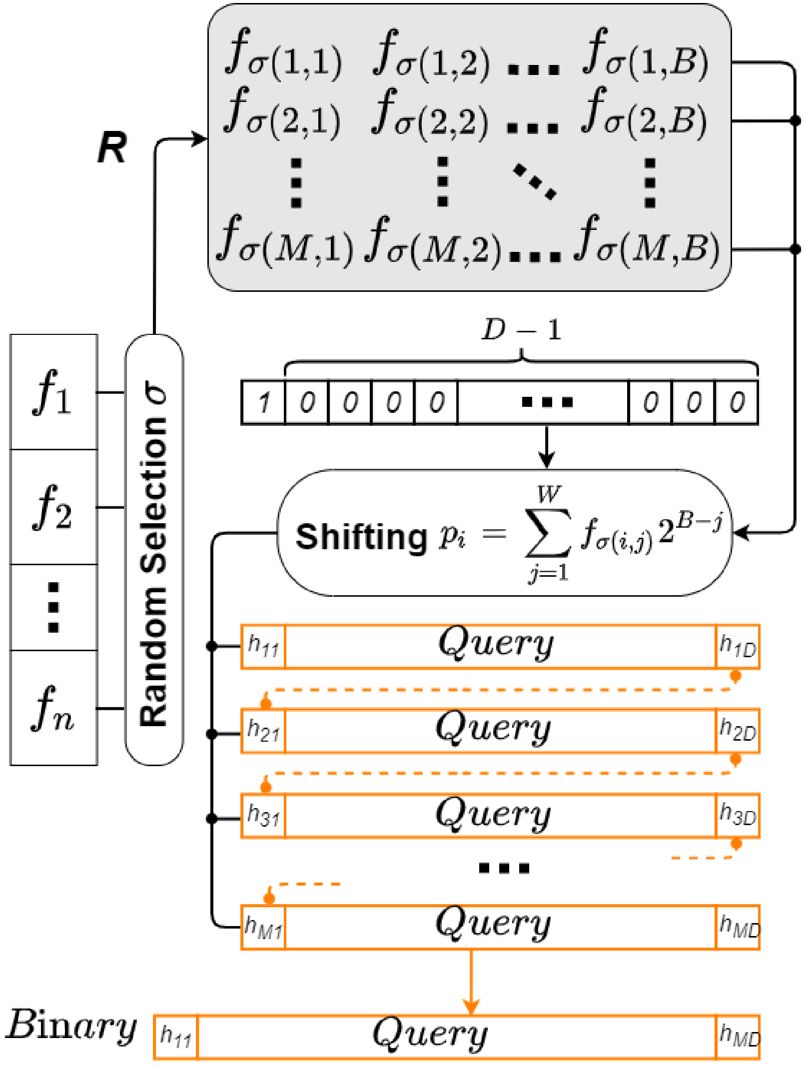
1. **Feature Extraction**
2. **Proposed Encoding**
3. **Training & Inference**
4. **Optimized Model Sparsification**

DistriHD Architecture(1/4) — Feature Extraction

- **Max-pooling**
- **Receptive Field**
  - Generate L_r distributed input patterns with non-binary elements.
- **Thermometer Binarization**
  - $L_r \rightarrow L_b \times L_r$ distributed input patterns with binary elements.



DistriHD Architecture(2/4) — Proposed Encoding



- Randomly select $M \times B$ elements from the binary input patterns $[f_1, f_2, \ldots, f_n]$ and construct the metric R
- For each row of R as an integer p_i in binary format, getting M binary vectors with D dimensions.
- Connect these M vectors to a single binary hypervector

  $H = [h_{11}, \ldots, h_{1D}, h_{21}, \ldots, h_{MD}]$

DistriHD Architecture(2/4) — Proposed Encoding

✓Eliminate the costly CiM and iM blocks.

- In traditional encoding of HD computing, according to the feature index and value, read the index hypervector and base hypervector from the pre-stored CiM and iM block.
- Example of Inference Memory Occupations in work [1].

	MNIST	ISOLET	UCIHAR	FACE
CiM	94.92%	91.41%	92.73%	94.70%
iM	3.87%	4.74%	5.29%	4.98%
AM	1.21%	3.85%	1.98%	0.31%

Expensive!

[1] M. Imani et al., "A Binary Learning Framework for Hyperdimensional Computing," in DATE, 2019.

DistriHD Architecture(3/4) — Training & Inference

- **Single-pass Training:** The distributed hypervectors from the same class are accumulated in the distributed class hypervectors.

- **Inference:** Check the similarity of the *L* distributed hypervectors.

Mathematically, the similarity metric in the traditional HD [1] is Hamming distance δ :

$$\sum_{l=0}^{L} \delta(H^l, C^l)$$

Similarity metric in the *DistriHD* is as follow:

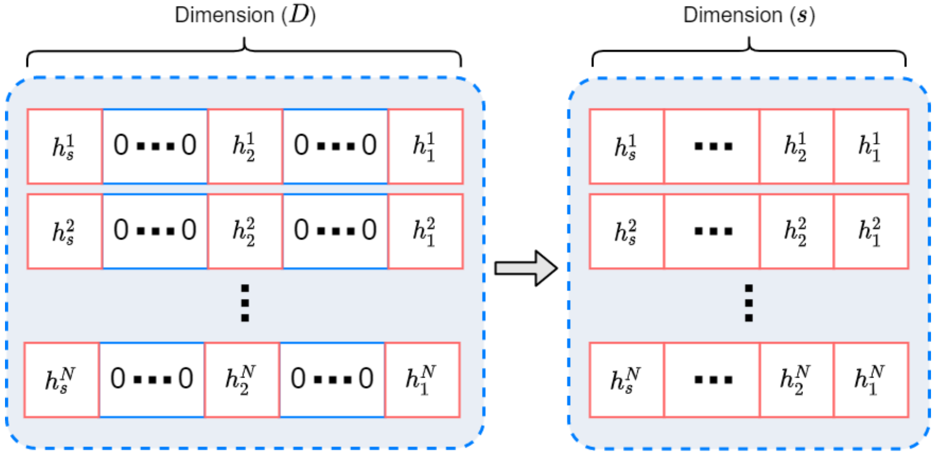
$$\sum_{l=0}^{L} \mathrm{sgn}[\, \delta\left(H^l \& C^l, C^l\right) - M]$$

[1] M. Imani et al., "A Binary Learning Framework for Hyperdimensional Computing," in DATE, 2019.

DistriHD Architecture(4/4) — Optimized Model Sparsification

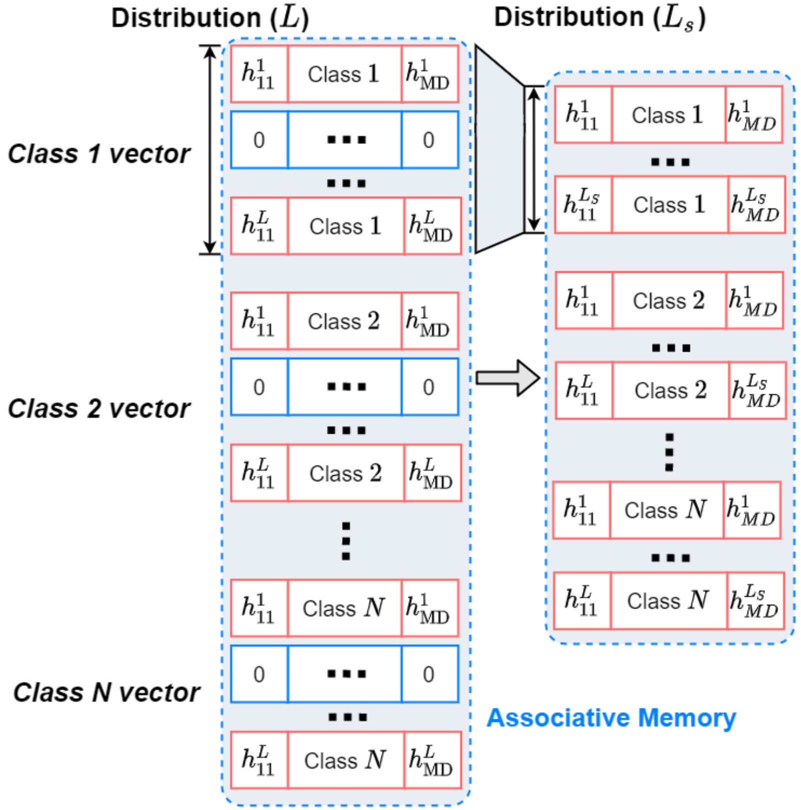
- Traditional HD

Dimension-wise Sparsification[1]



- *DistriHD*

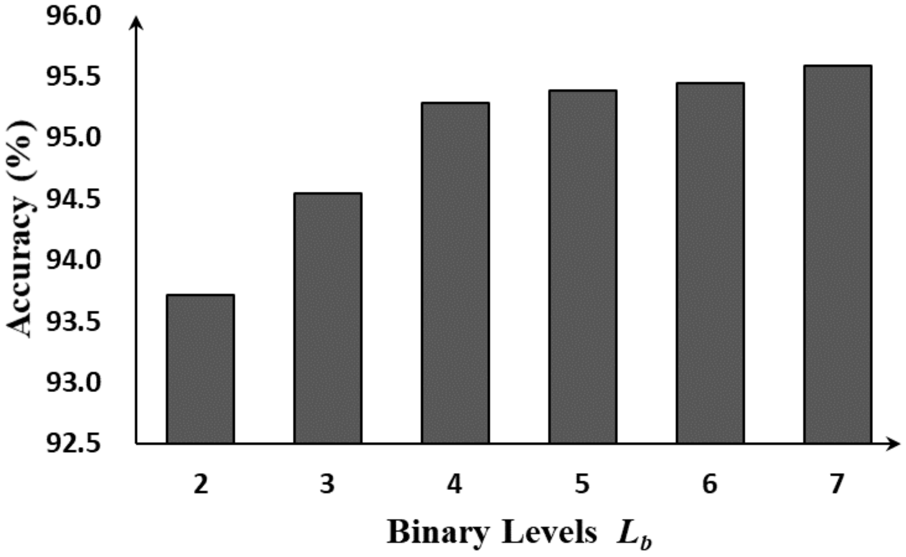
Additional Feature-wise Sparsification

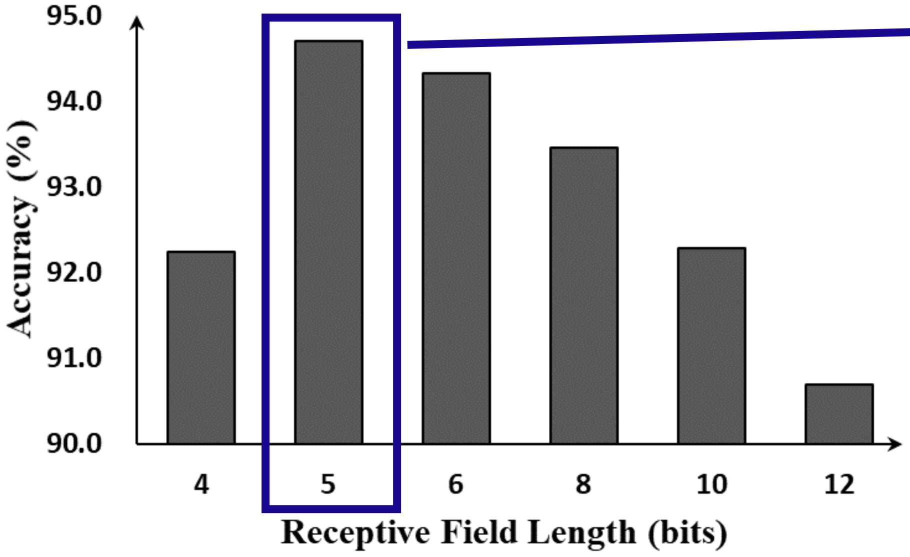


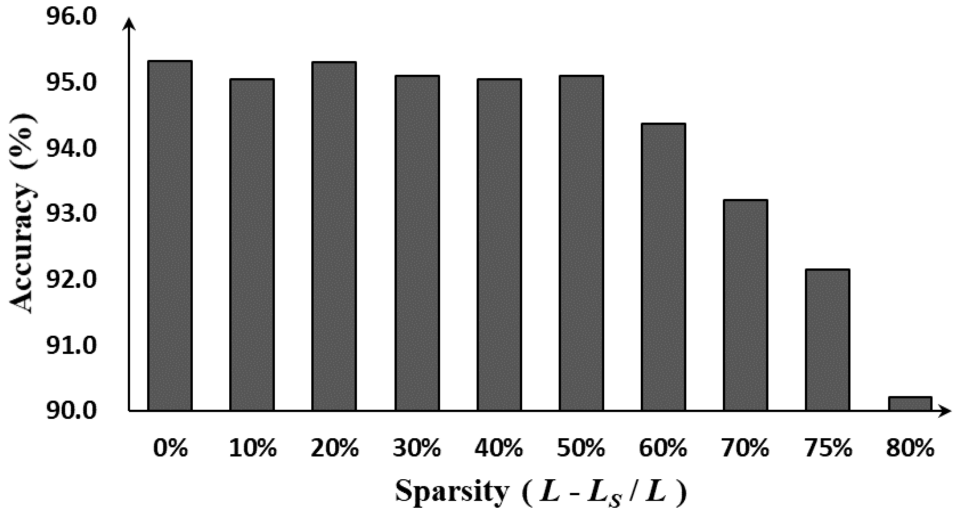
[1] M. Imani et al., "SparseHD: Algorithm-Hardware Co-Optimization for Efficient High-Dimensional Computing," in FCCM, 2019.

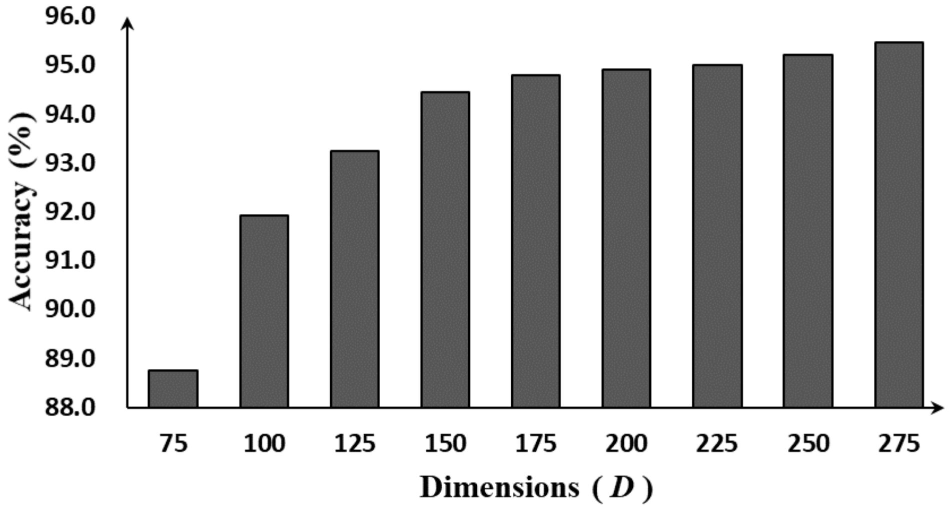
Experimental Results(1/3) —
Impact of Parameters in *DistriHD*

Parameter Tuning









Experimental Results(2/3) — Memory Cost Reduction

- The memory cost reduction mainly comes from the elimination of CiM and iM.

1. including iM:

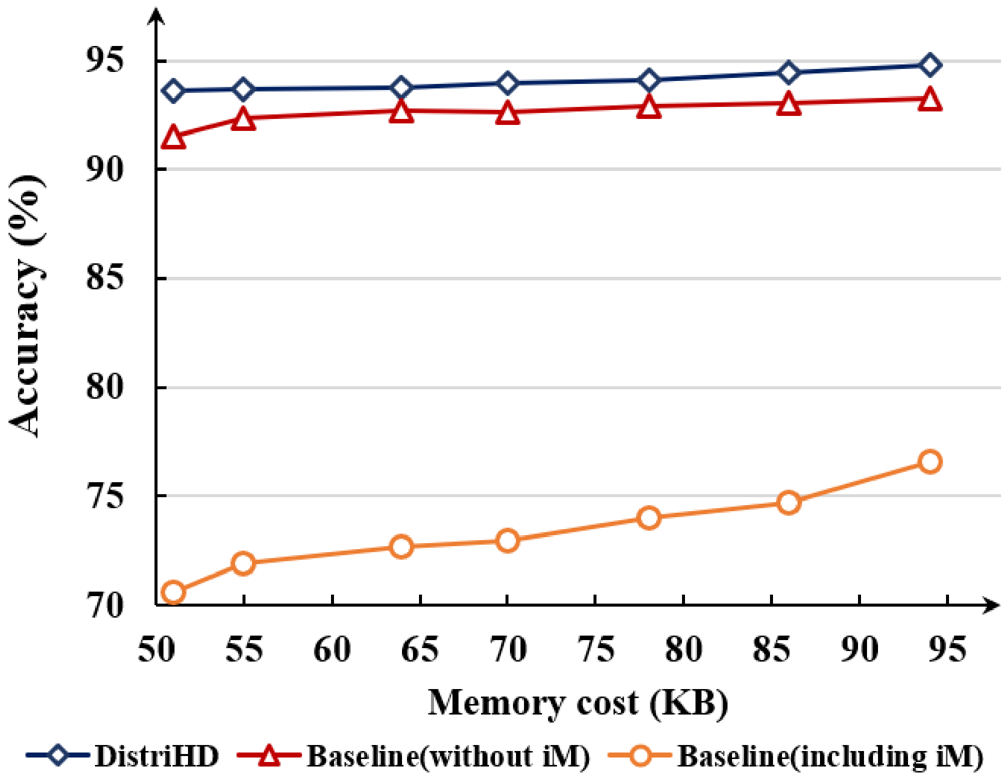
(Baseline[1] Memory Cost = CiM+iM+AM)

Achieve **27.6x** reduction in inference memory cost without hurting the accuracy.

2. without iM:

(Baseline Memory Cost = AM)

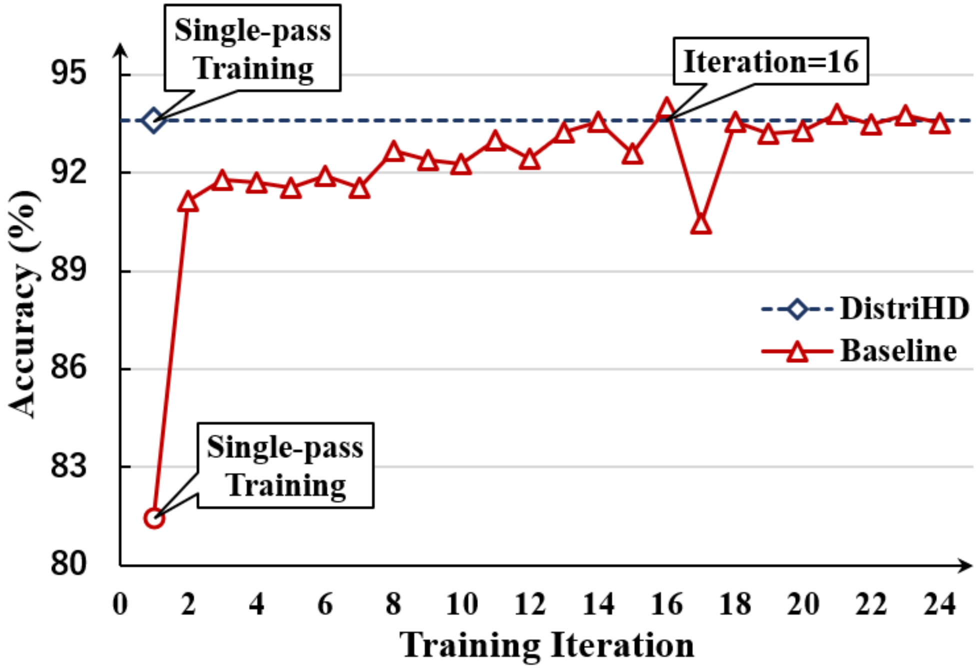
Achieve a similar accuracy.



[1] M. Imani et al., "A Binary Learning Framework for Hyperdimensional Computing," in DATE, 2019.

Experimental Results(3/3) — Training Iteration & Hardware Cost

- Efficient **Single-Pass** Training:
- (*DistriHD* vs 50*Baseline[1])



- Hardware Comparison:
  - **9.9x** and **28.8x** reduction in area and power, respectively.

[1] M. Imani et al., "A Binary Learning Framework for Hyperdimensional Computing," in DATE, 2019.

Conclusion

- Utilize **binary** hypervectors in both training and inference phase.
- Successfully eliminate the costly CiM and iM in the encoding procedure, resulting in **27.6x inference memory reduction** without hurting the accuracy.
- Training process can be accomplished in **single-pass** way.
- **9.9x** and **28.8x** reduction in **area** and **power**, respectively.