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SHAPING THE NEXT GENERATION OF ELECTRONICS

JUNE 23-27, 2024

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SMORE: Similarity-based Hyperdimensional Domain Adaptation for Multi-Sensor Time Series Classification

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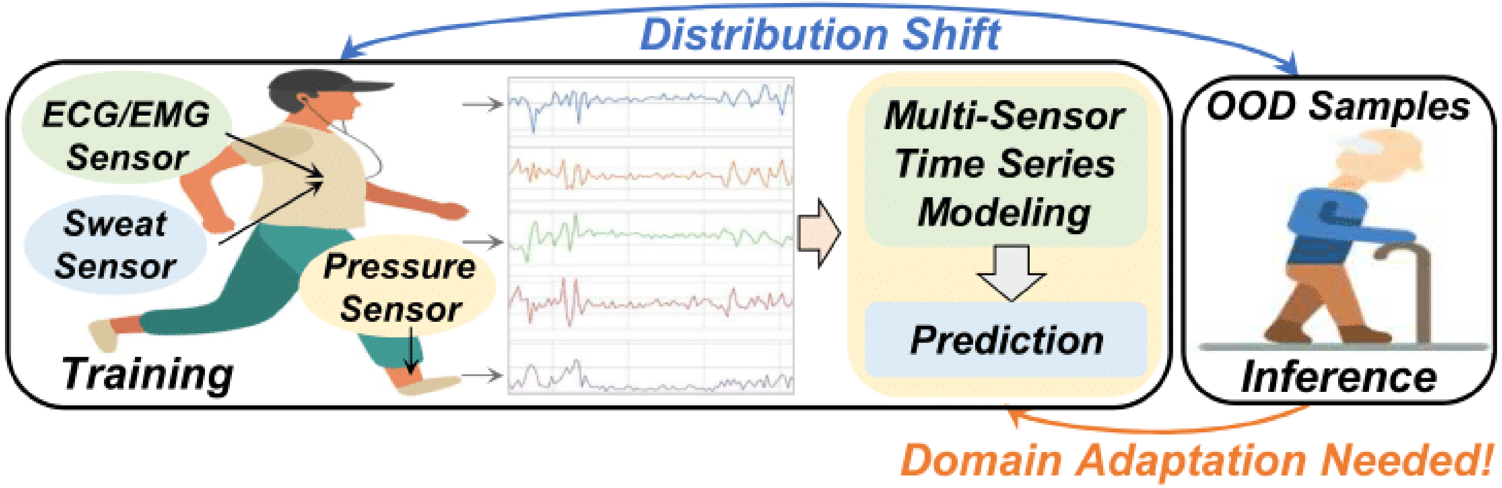
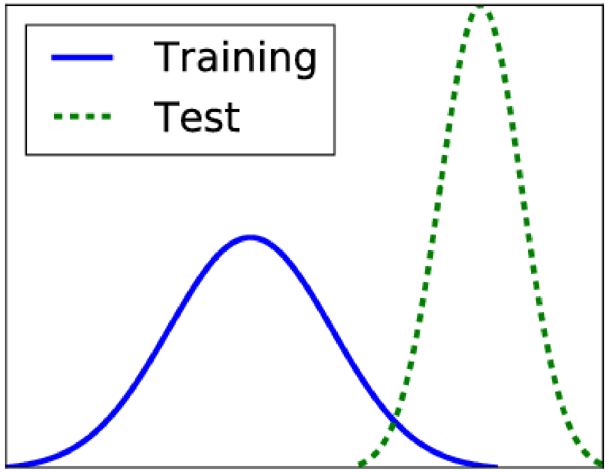
Distribution Shift

- *Distribution shifts* occurs when the joint distributions of inputs and outputs differ between training and test stages, i.e., $p_{train}(\mathbf{x}, y) \neq p_{test}(\mathbf{x}, y)$.
  - **Source domain(s):** the domain(s) from which the training data is collected
  - **Target domain:** the domain where the model is deployed or tested
  - Out-of-distribution (OOD) samples are unavoidable during deployment in the real world.

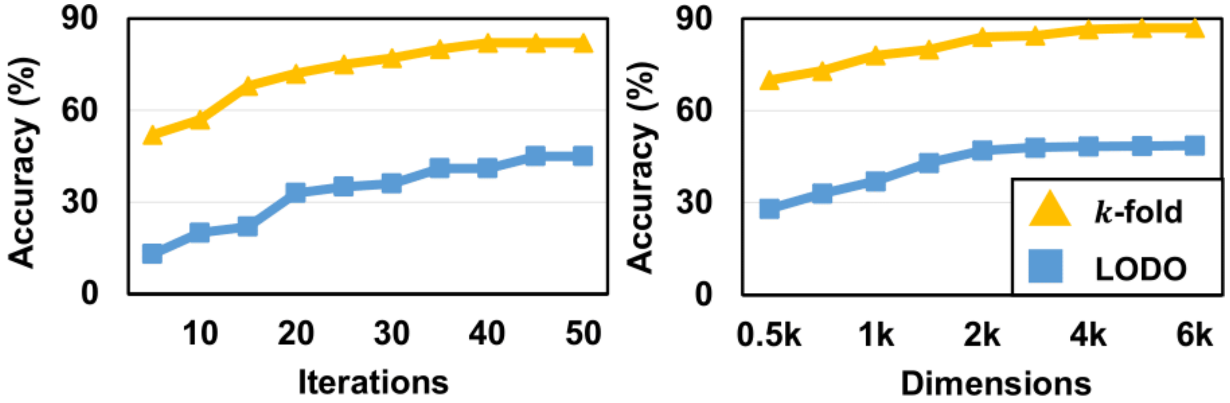




OOD: out-of-distribution

Problem Overview

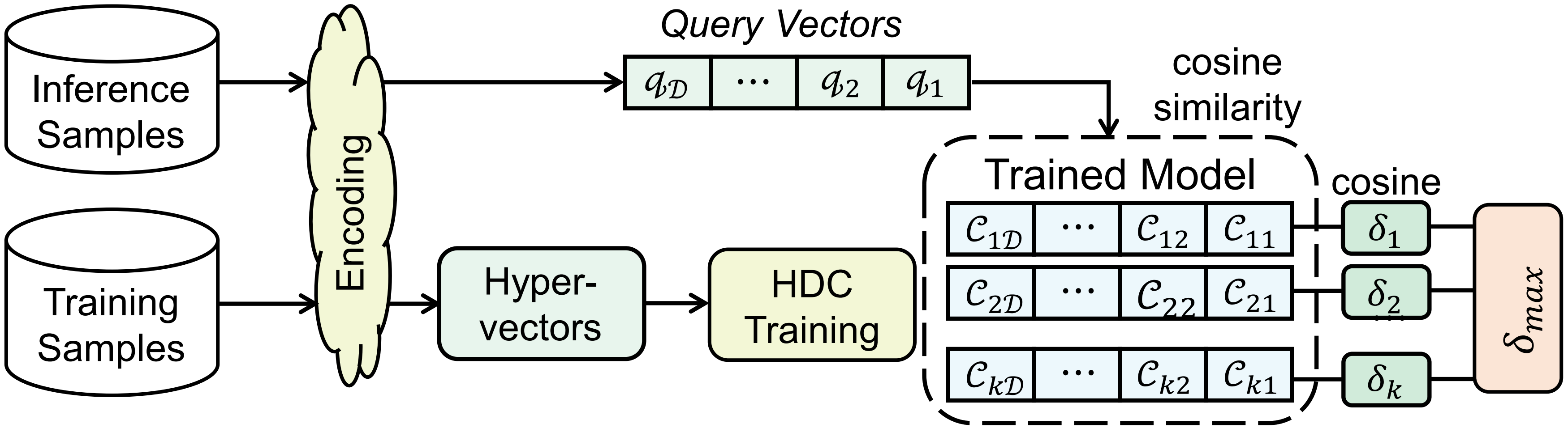
- We target the distribution shifts problem in *multi-domain time series* classification in *embedded system*
  - e.g., human activity recognition based on multi-sensor time series data
- **Challenges:** SOTA DNN-based domain adaptation techniques are *computation expensive* for real-time time-series classification tasks
- We leverage hyperdimensional computing (HDC) for efficient domain adaptation



There is a huge gap between leave-one-domain-out (LODO) cross-validation and standard k-fold (leave-one-out) cross validation regardless of training iterations and model complexity, indicating very limited domain adaptivity in prior works.

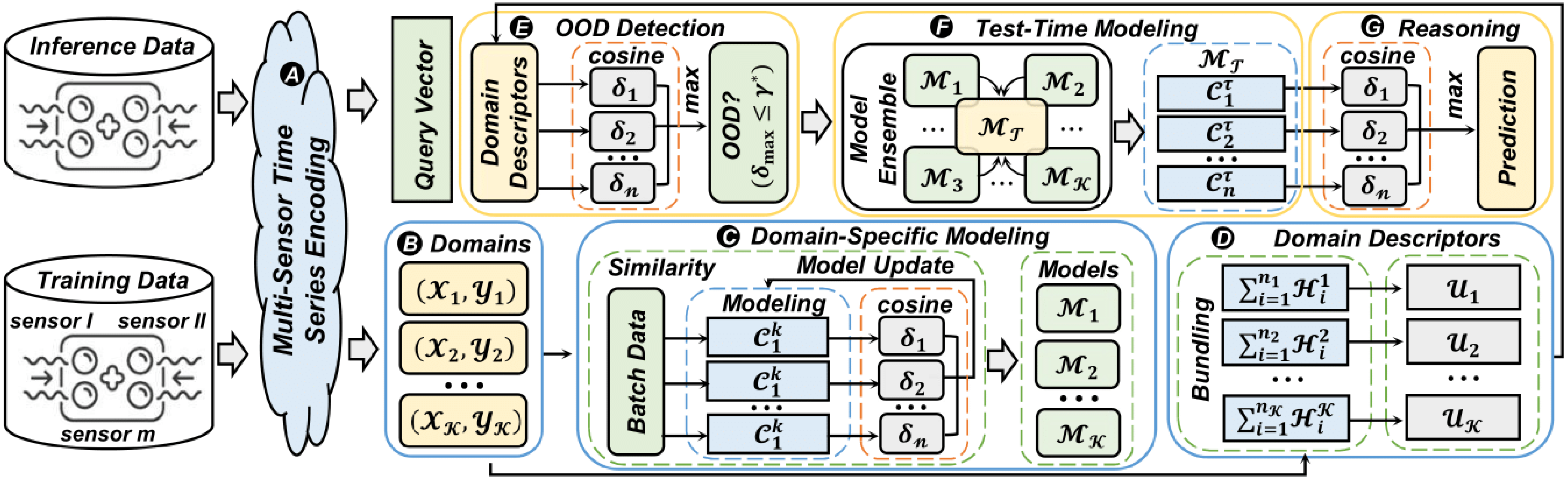
Hyperdimensional Computing

- Hyperdimensional computing has been introduced for: faster convergence, high computational efficiency, and robustness against noises.
- Projecting low-dimensional inputs to high-dimensional space
- Construct class hypervectors in high-dimensional space
- Perform classification tasks by calculating similarity scores



SMORE

- Encoding
- Training:
  - Domain Specific Modeling
  - Domain Descriptors
- Testing:
  - Out-of-Distribution Detection
  - Model Ensemble
  - Reasoning

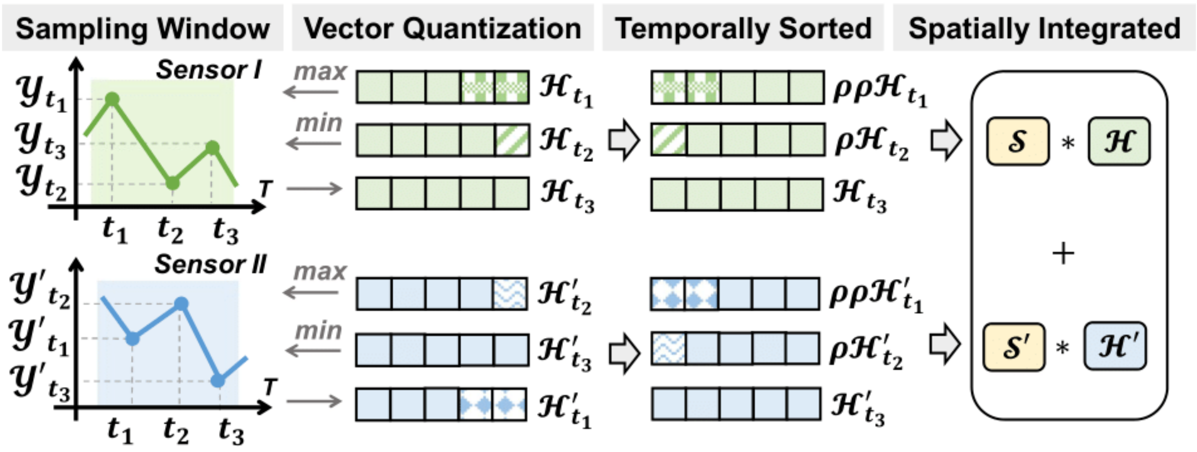


SMORE: Encoding

- We follow the common time series encoding technique used in recent HDC works.
- Assign random hypervectors $\mathcal{H}_{max}$ and $\mathcal{H}_{min}$ to represent the maximum and minimum signal values, i.e., y_{max} and y_{min}.
- Vector quantization to values between y_{max} and y_{min}, e.g.,

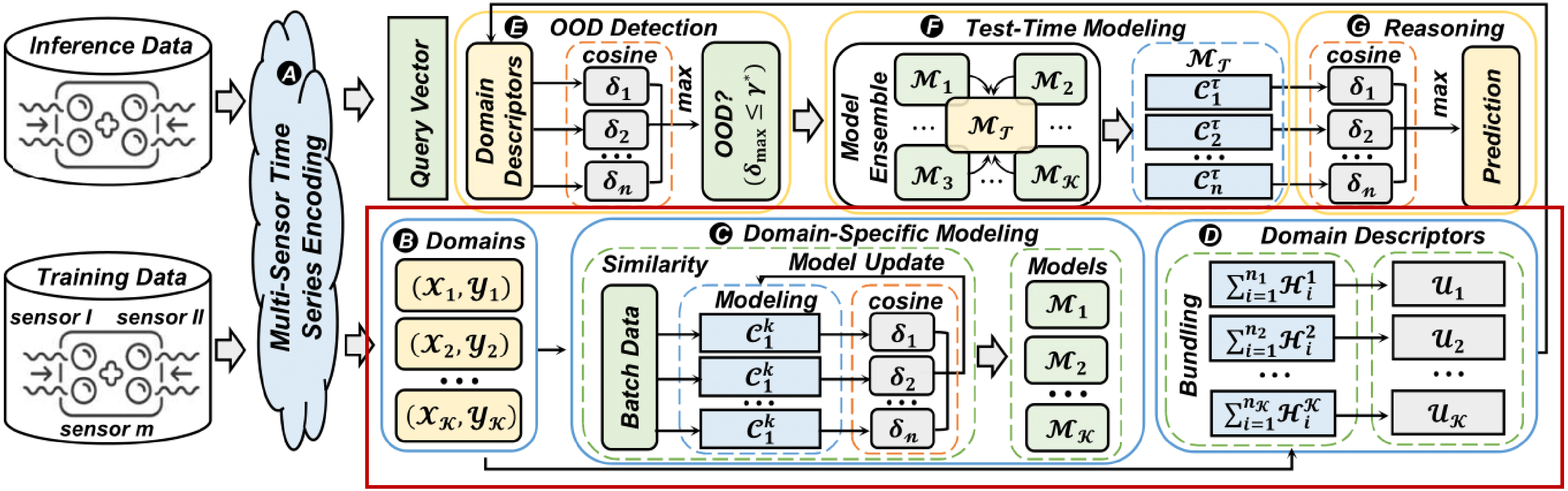
$$\mathcal{H}_{t_3} = \mathcal{H}_{t_2} + \frac{y_{t_3} - y_{t_2}}{y_{t_1} - y_{t_2}} \cdot (\mathcal{H}_{t_1} - \mathcal{H}_{t_2});\ \mathcal{H'}_{t_1} = \mathcal{H'}_{t_3} + \frac{y'_{t_1} - y'_{t_3}}{y'_{t_2} - y'_{t_3}} \cdot (\mathcal{H'}_{t_2} - \mathcal{H'}_{t_3})$$

- Temporally sorting by rotation shifts (ρ), e.g., $\mathcal{H} = \rho\rho\mathcal{H}_{t_1} * \rho\mathcal{H}_{t_2} * \mathcal{H}_{t_3}$
- Spatially integrating by binding, e.g., $\mathcal{H} = \mathcal{S}_1 * \mathcal{H}_1 + \cdots + \mathcal{S}_n * \mathcal{H}_n$



SMORE: Training

- ***Domain-specific Models***: individual HDC models for each domain
- ***Domain Descriptors***: hypervectors representing each domain



SMORE: Training

- Domain-Specific Models: individual HDC models for each domain
  - Separate training samples into subsets based on their domains
  - In each domain specific model:
    - n class hypervectors, $n =$ the number of classes
    - A new sample $\mathcal{H}$ in the domain updates the model based on its cosine similarity δ
    - If $\mathcal{H}$ has the highest similarity score with the class hypervector $\mathcal{C}_i$ while its true label $\mathcal{C}_j$:

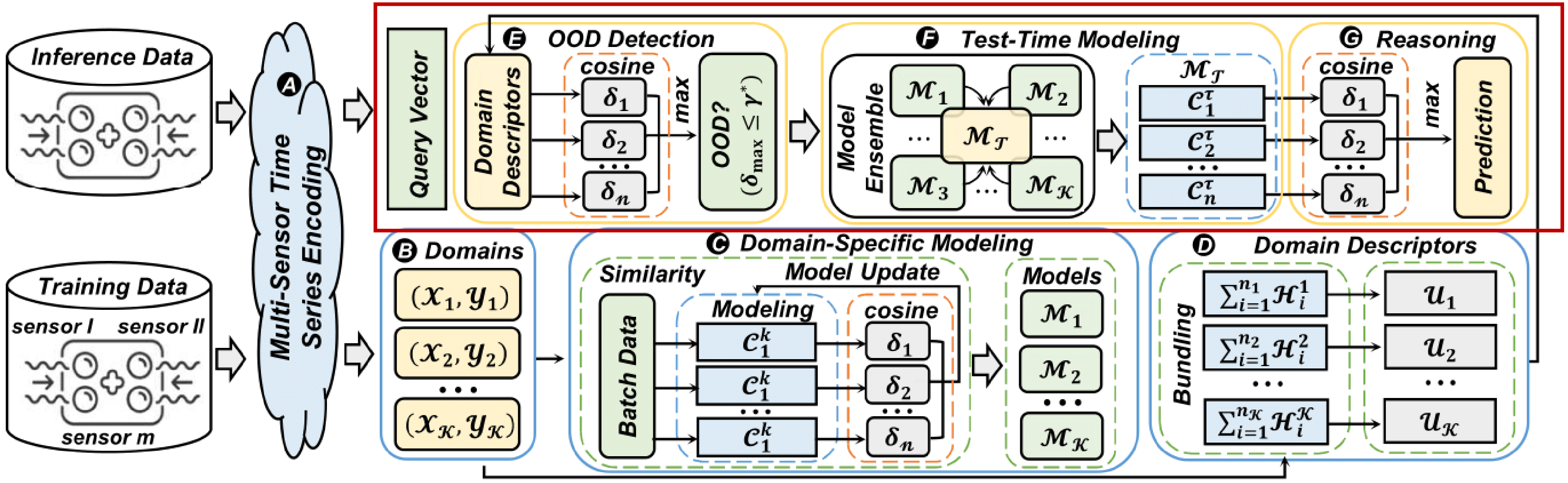
$$\mathcal{C}_i = \mathcal{C}_i - \eta \cdot \big(1 - \delta(\mathcal{H}, \mathcal{C}_i)\big) \times \mathcal{H}$$

$$\mathcal{C}_j = \mathcal{C}_j + \eta \cdot \Big(1 - \delta\big(\mathcal{H}, \mathcal{C}_j\big)\Big) \times \mathcal{H}$$

- Domain Descriptors: hypervectors representing each domain
  - For each domain, bundle (elementwise add) all the hypervectors within the domain
  - k hypervectors, $k =$ the number of domains

SMORE: Testing

- Out-of-Distribution Detection
- Adaptive Model Ensemble



SMORE: Testing

- Similarity Check:
  - Calculate the similarity scores $(\delta_1, \ldots, \delta_k)$ between the testing sample and each domain descriptors
- Out-of-Distribution (OOD) Detection
  - The sample will be identified as OOD if $\max\{\delta_1, \ldots, \delta_k\}$ is lower than a threshold δ^*
- Adaptive Time-Test Model Ensemble
  - For OOD testing sample:
    - Form new class hypervectors by ensemble all domain-specific models based on similarity to include more comprehensive info and provide the best prediction
  - For in-distribution samples:
    - Only ensemble domain-specific models that the sample is highly similar to, other domain-specific models will be treated as noises
- Prediction

Experimental Results

- Baseline Models：
  - Two SOTA CNN-based domain adaptation methods:
    - TENT [1]
    - MDANs [2]
  - BaselineHD[3]: SOTA HDC algorithm not considering distribution shifts
  - DOMINO[4] : SOTA HDC-based domain generalization algorithm

- Evaluations
  - Accuracy
  - Efficiency
  - Scalability

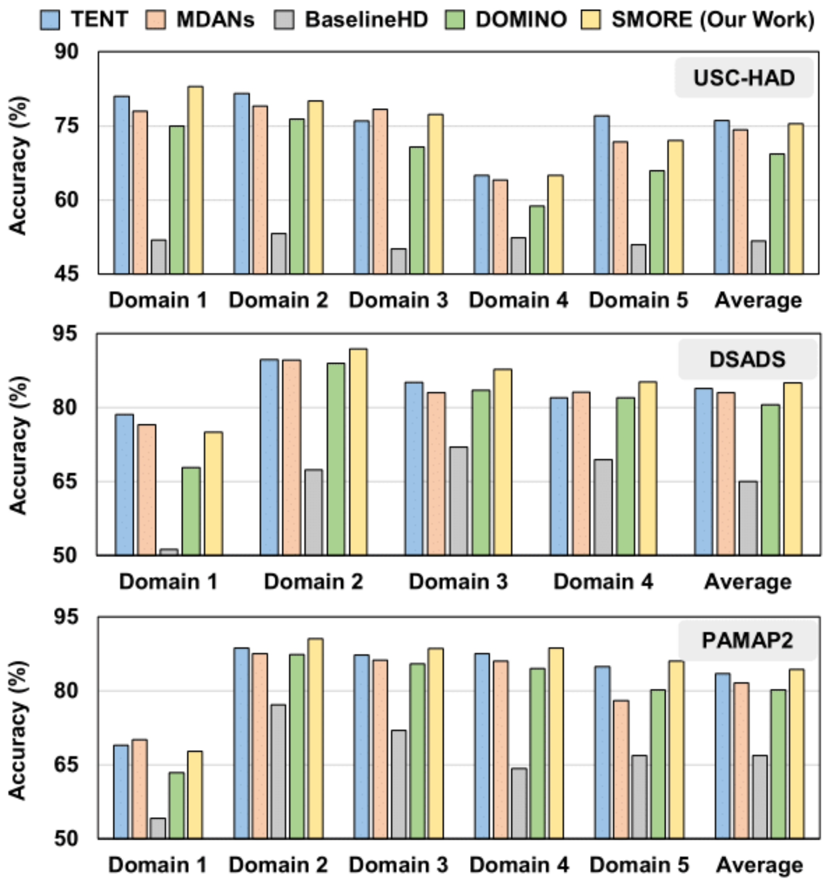
Table 1: Detailed Breakdowns of Datasets
($\mathcal{N}$: number of data samples)

DSADS [20]		USC-HAD [13]		PAMAP2 [21]	
Domains	$\mathcal{N}$	Domains	$\mathcal{N}$	Domains	$\mathcal{N}$
Domain 1	2,280	Domain 1	8,945	Domain 1	5,636
Domain 2	2,280	Domain 2	8,754	Domain 2	5,591
Domain 3	2,280	Domain 3	8,534	Domain 3	5,806
Domain 4	2,280	Domain 4	8,867	Domain 4	5,660
		Domain 5	8,274		
Total	9,120	Total	43,374	Total	22,693

[1] Dequan Wang et al. Fully test-time adaptation by entropy minimization. In ICLR, 2020
[2] Han Zhao et al. Multiple source domain adaptation with adversial learning. In ICLR, 2018.
[3] Alejandro Hernandez-Cano et al. OnlineHD: Robust, efficient, and single-pass online learning using hyperdimensional system, DATE, 2021
[4] Junyao Wang, et al. Domino: Domain-invariant hyperdimensional classification for multi-sensor time series data, ICCAD, 2023

Experimental Results

Accuracy:



On average:

Comparable accuracy to TENT

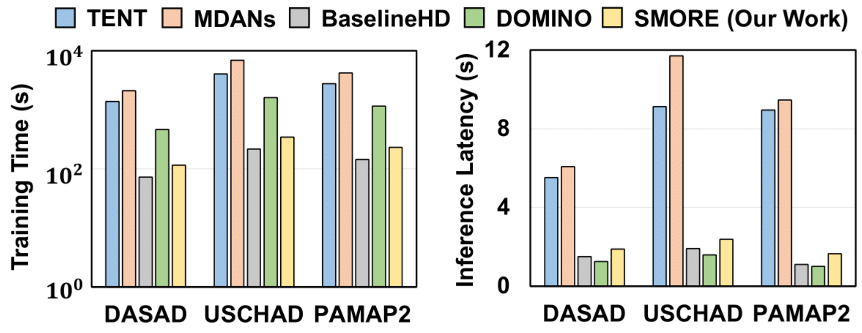
1.98% higher accuracy than MDANs

20.25% higher accuracy than BaselineHD

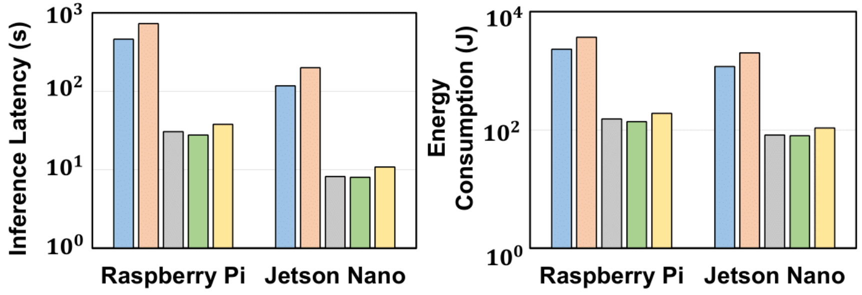
4.56% higher accuracy than DOMINO

Experimental Results

Efficiency:

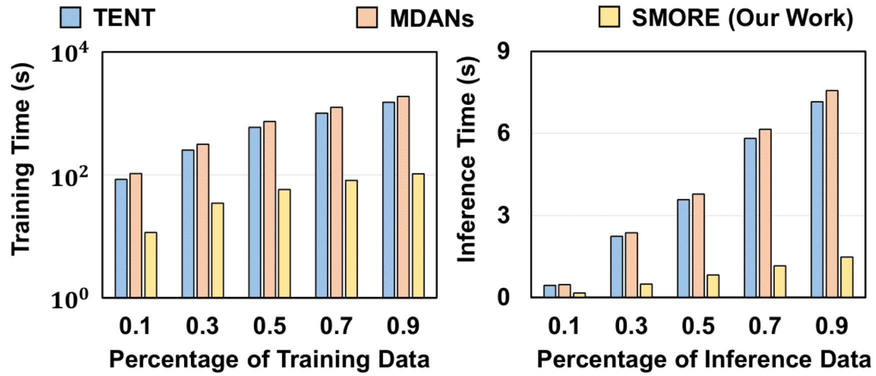


(a) Efficiency of SMORE and CNN-based Algorithms on Server CPU



(b) Efficiency of SMORE and CNN-based Algorithms on Edge Platforms

Scalability:



- Training:
  - 11.64× faster than TENT, 18.81× faster than MDANs, 5.84 × faster than DOMINO
- Testing:
  - 4.07× faster than TENT, 4.63× faster than MDANs.

Conclusion

- We developed an innovative HDC-based domain adaptation technique that
  - Explicitly consider distribution shifts in the testing time
  - Efficiently adapt a trained model to potential distribution shits in testing

Thank you for your attention!

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