Renmin University of China

As-ECTS: Adaptive Shapelet Learning for Early Classification of Streaming Time Series

Paper ID: 401

Agenda

01 Introduction

Background

Time series are numerical sequences with temporal relations and semantics.

- Early Classification of Time Series (**ECTS**) predicts class labels before the complete sequence is observed, enabling timely decision-making.
- In practice, ECTS has been widely applied in time-sensitive scenarios.
  - **Medical Diagnosis**: Early detection of ECG.
  - **Industrial Monitoring**: Real-time warning of anomalies.

Data Formulation

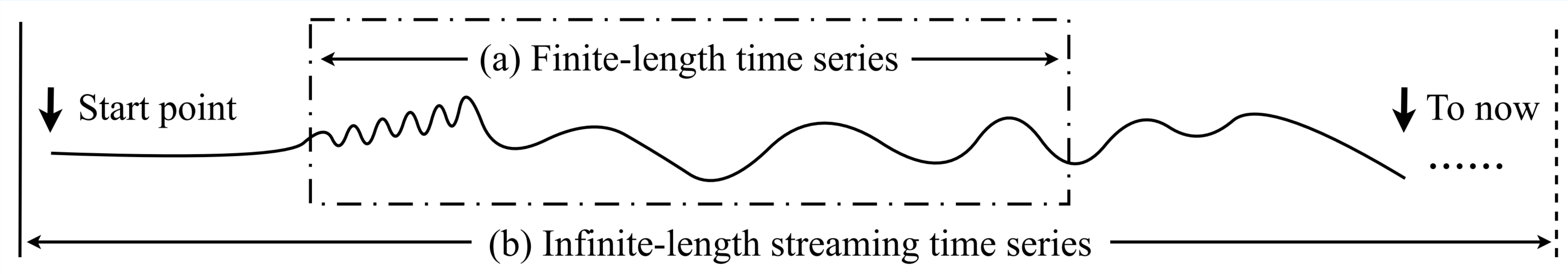

Fig. 1: Illustration of finite-length and infinite-length streaming time series.

Existing methods assume fixed-length time-series segments (Fig. 1 (a)), whereas real-world data are continuous and potentially infinite streams (Fig. 1 (b)).

Task Formulation

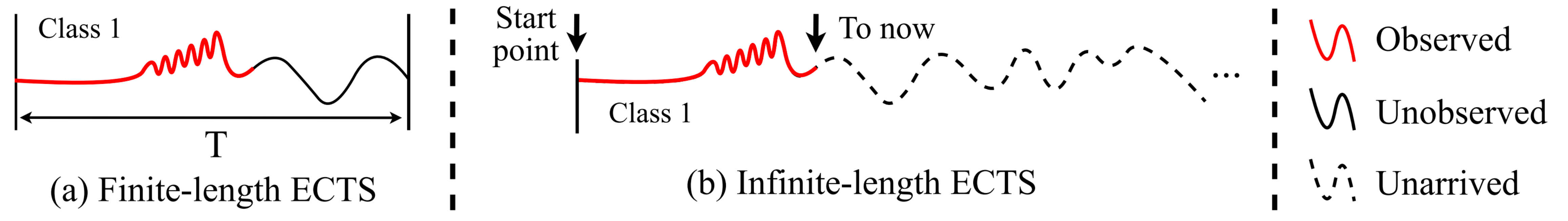

Fig. 2: Finite-length and infinite-length ECTS

Most ECTS methods implicitly assume finite-length inputs (Fig. 2 (a)), but real-world data often comes as infinite streams with evolving distributions (Fig. 2 (b)). Adapting to this dynamic, unbounded streaming time series is a research difficulty.

Problem

Existing ECTS methods struggle to continuously obtain reliable labels for the current state through early classification from incomplete observations of streaming time series.

Challenge

- Challenge 1 — **Adaptive Stream Modeling**

Continuously modeling evolving historical distributions under limited memory.

- Challenge 2 — **Efficient and Interpretable ECTS**

Achieving reliable early classification with low computational cost.

Insight & Motivation

Shapelets are discriminative and interpretable subsequences that capture temporal patterns, making them well suited for adaptive stream modeling and efficient, interpretable ECTS. However, existing shapelet-based methods are costly for streaming ECTS.

Contribution

- Design a Shapelet Similarity Matrix for **Adaptive Stream Modeling**.
- Develop an Early Shapelet Classifier for **Efficient and Interpretable ECTS**.
- Experiments demonstrating State-of-the-art Accuracy–Earliness Harmonic Mean.

02 As-ECTS Framework

As-ECTS Framework

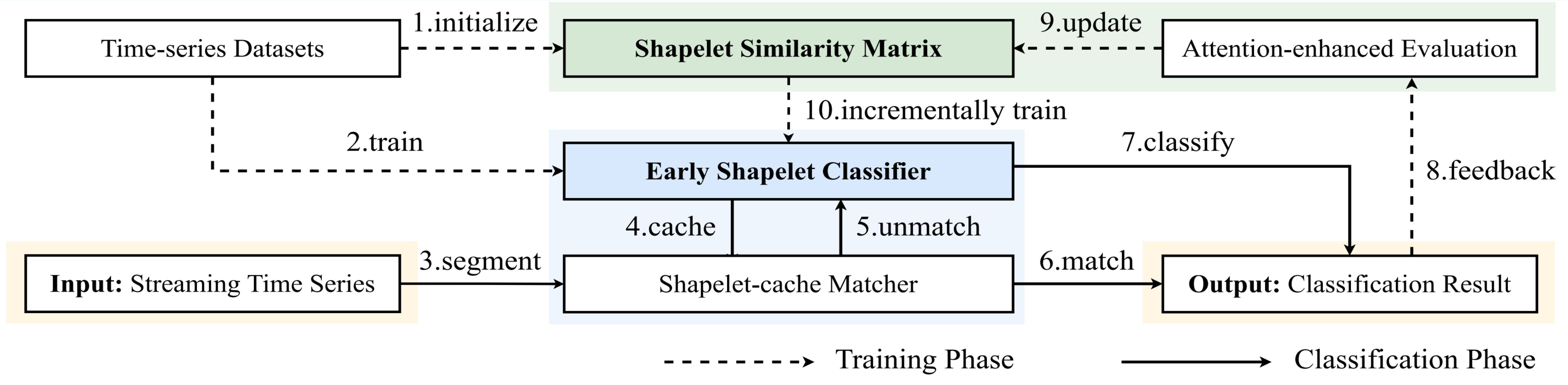

Fig. 3: Overview of the As-ECTS framework

- **Training Stage (1,2,8,9,10):** Initialize the classifier and matrix, then incrementally update the matrix with attention-enhanced feedback for adaptive streaming ECTS.
- **Early Classification Stage (3,4,5,6,7):** Match current observations with cached shapelets to achieve efficient and interpretable streaming ECTS.

Shapelet Similarity Matrix

- Matrix Construction: Construct a shapelet similarity matrix to store the similarity of temporal distribution of discriminative shapelets from streaming time series.

- Shapelet Similarity: Measure shapelet similarity to capture temporal pattern relationships and distributional evolution through shapelet similarity.

- Matrix Update: Incrementally update the matrix via attention-enhanced feedback to adaptively preserve important patterns and track evolving streams.

Early Shapelet Classifier

- Random Shapelet-Cache Forest: Build an efficient and interpretable ensemble classifier with diverse cached shapelets by storing diverse discriminative shapelets.

- Shapelet-Cache Matcher: Directly match current observations with cached shapelets for fast and interpretable early classification.

- Incremental Training: Continuously update shapelet caches with new observations to adapt the classifier to evolving streams.

03 Experiments

Experiment Setting

- Datasets: PTB-XL, UCR, and Smart Home with diverse lengths and class numbers.

- Baselines:
  - ECTS is a pioneering early classification method.
  - EDSC/ECDIRE/MSLM are interpretable shapelet-based methods.
  - ECDIRE supports streaming pattern detection.
  - MSLM handles finite- and infinite-length time series.

- Metrics: earliness, accuracy, and their harmonic mean (HM).

Experiment Analysis

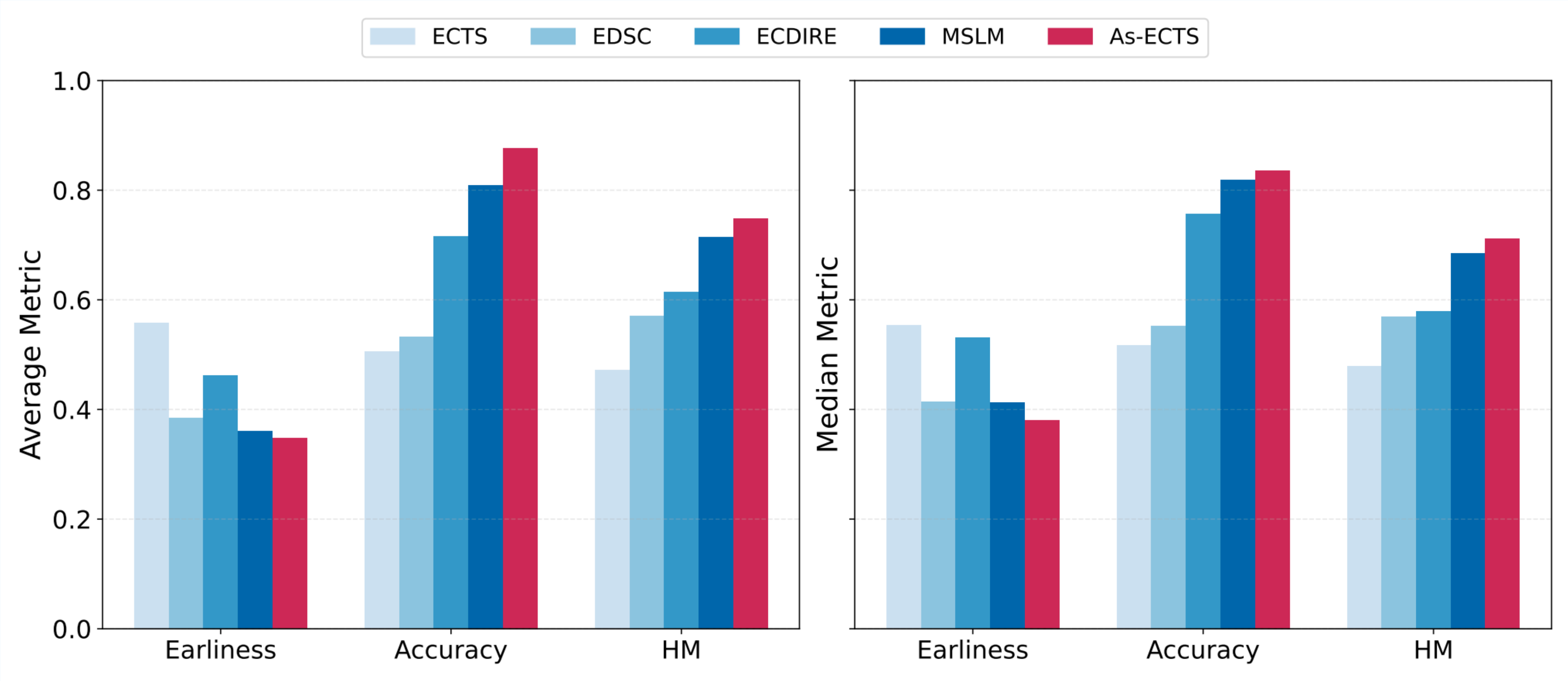

Fig. 4: Comparison of AS-ECTS and Baselines on Average and median metrics.

- Improves HM by 58.7% over ECTS and accuracy by 8.4% over MSLM.

Experiment Analysis

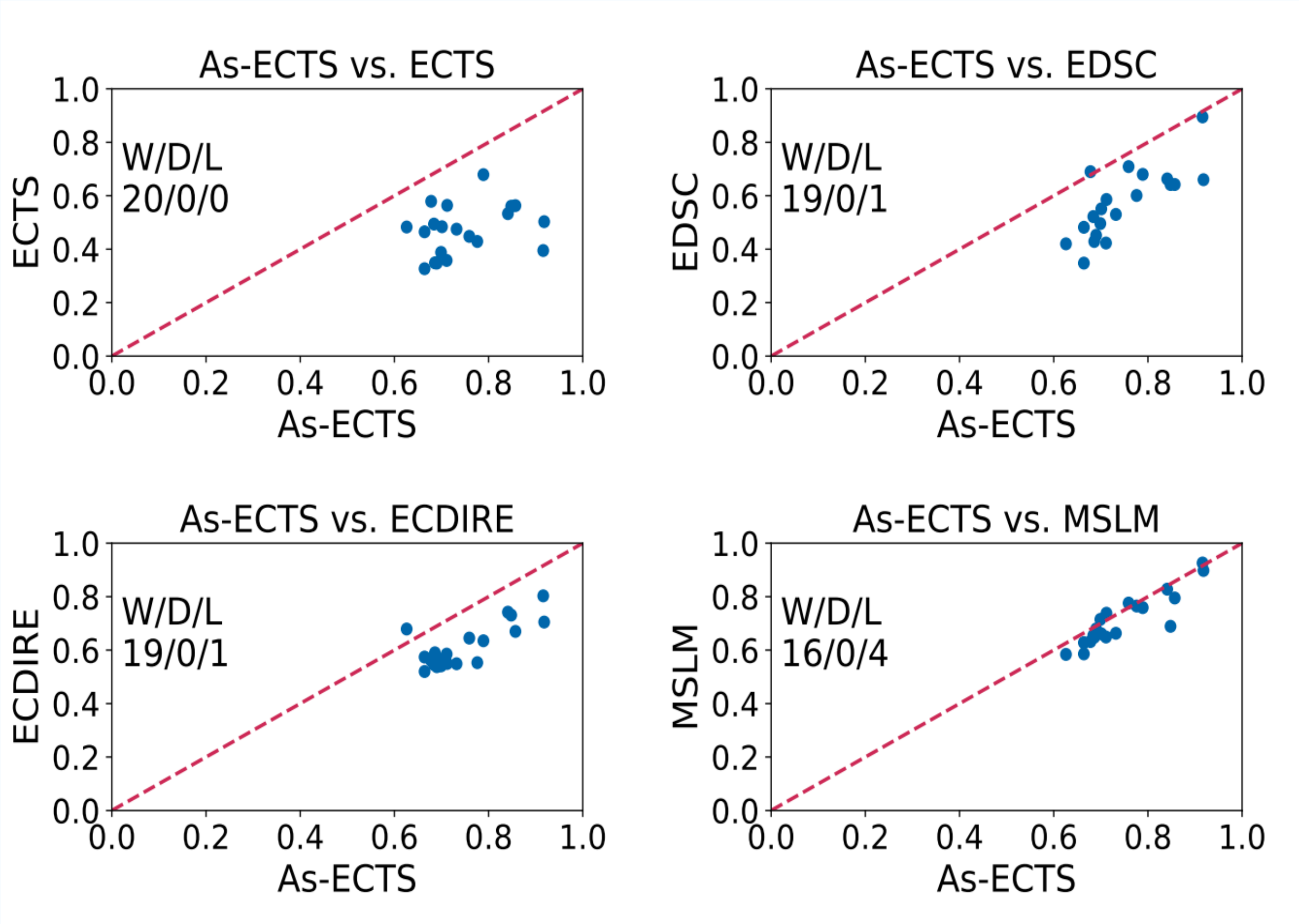

Fig. 5: As-ECTS vs. baselines.

- **Overall Superiority:**

As-ECTS wins 74/80 HM comparisons (92.5% win rate), demonstrating consistent superiority across datasets and baselines.

- **Competitive Performance:**

The few failures against MSLM occur on specific datasets with comparable accuracy–earliness.

Experiment Analysis

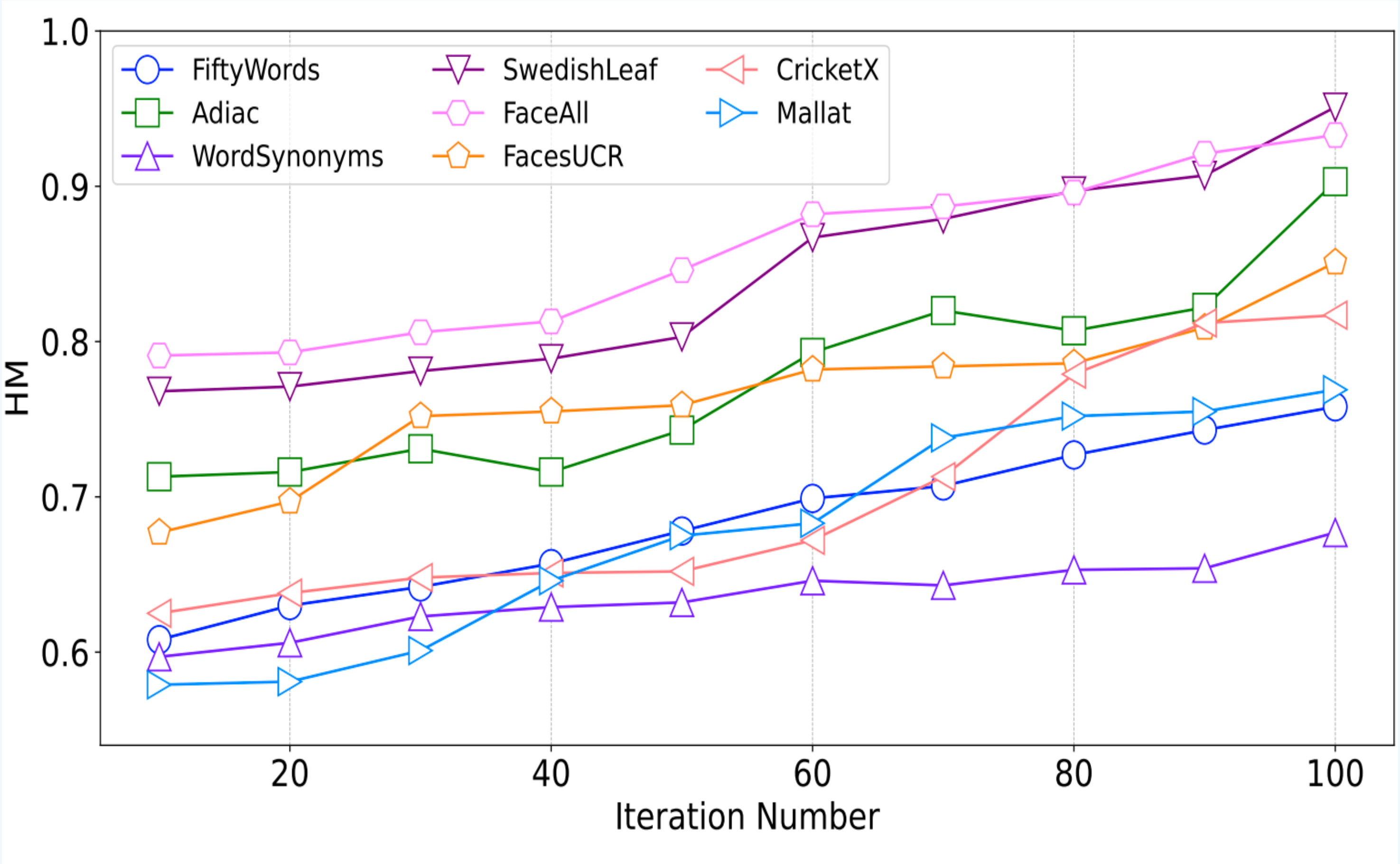

Fig. 6: Harmonic Mean (HM) metrics over iterations.

- **Continuous Improvement**：

HM increases with incremental iterations across datasets.

- **Dataset Dependent:**

Different datasets achieve gains at different stages.

- **Saturation Effect**：

Limited cache memory bounds further performance improvement.

Experiment Analysis

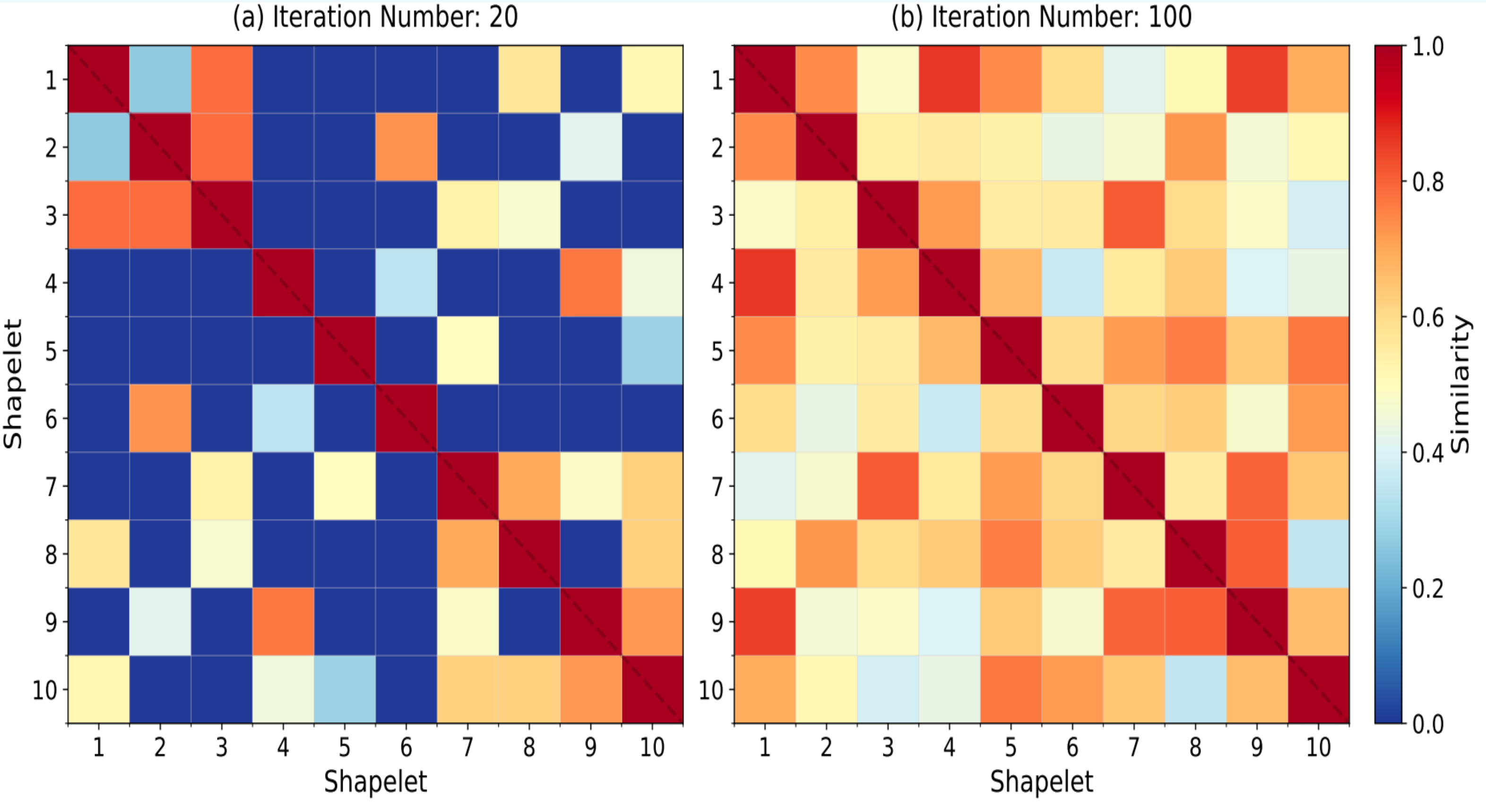

Fig. 7: Similarity evolution over iterations.

- **Progressive Coverage:**

Shapelet similarities progressively cover temporal patterns.

- **Adaptive Memory:**

Attention-enhanced updates preserve informative similarities under limited memory.

- **Streaming Adaptation:**

Iterative updates continuously adapt to evolving streams.

04 Conclusion & Future Work

Conclusion

We propose **As-ECTS**, an adaptive shapelet learning framework for streaming ECTS, with a **Shapelet Similarity Matrix** for adaptive stream modeling and an **Early Shapelet Classifier** for efficient and interpretable classification.

Future Work

A promising future direction is enhancing interpretability by integrating LLMs.

Q & A

Thank You

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