



Active learning for time instant classification

Nauman Ahad*, Namrata Nadagouda*, Eva L. Dyer, Mark A. Davenport

Contact: nahad3@gatech.edu, namrata.nadagouda@gatech.edu



Introduction

Active learning is a common strategy for reducing the dependency of model training on large labeled datasets by selecting only the most useful data for labeling.

Goal: Devise an active learning for acquiring labels

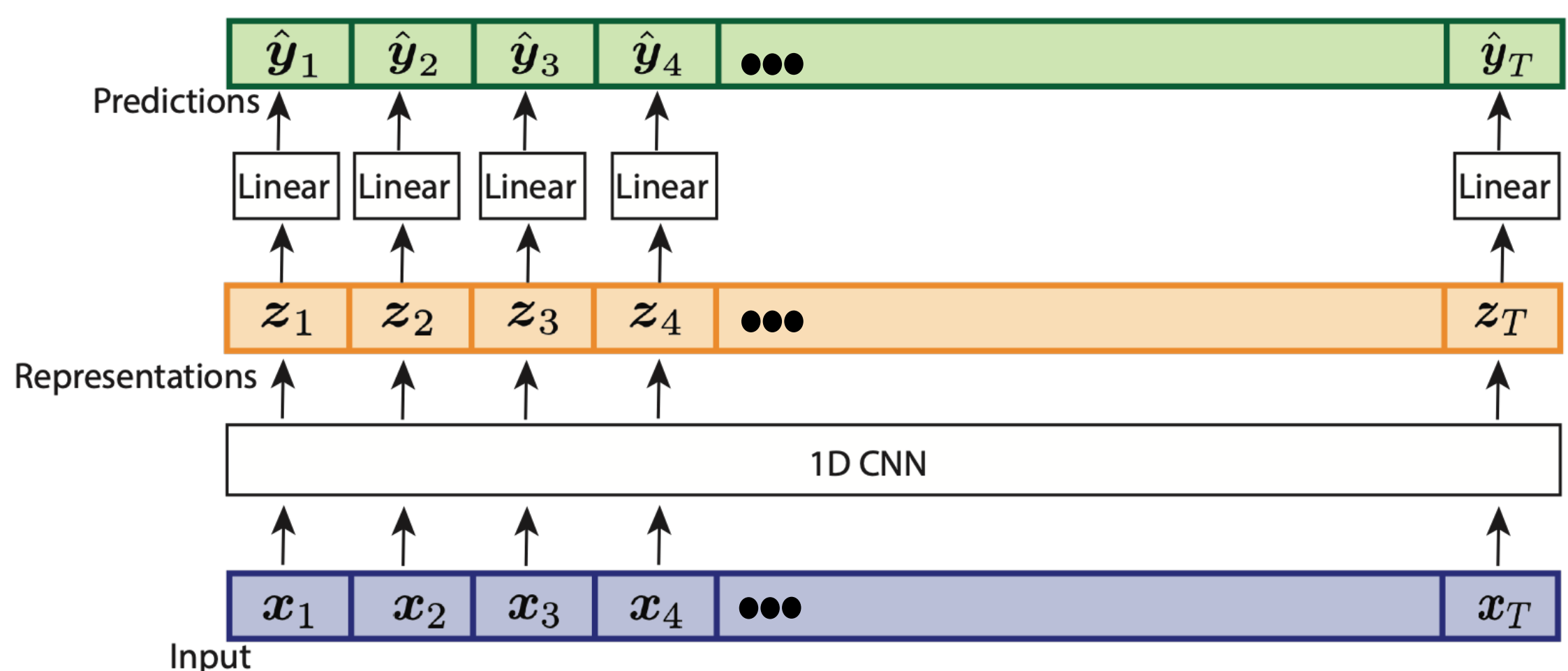
Prior work:

- Consider AL for time sequence classification
- Limited work on AL for deep networks

Problem setup

Each time instance $x_i \in \mathbb{R}^d$ in time series $X = \{x_1, \dots, x_T\}$ is to be classified in class y_i .

A 1D CNN transforms each point x_i in the input time series to a corresponding point, $z_i \in \mathbb{R}^m$, in the representation space. A linear layer followed by a softmax layer produces prediction probabilities $\hat{y}_i$.



Our method

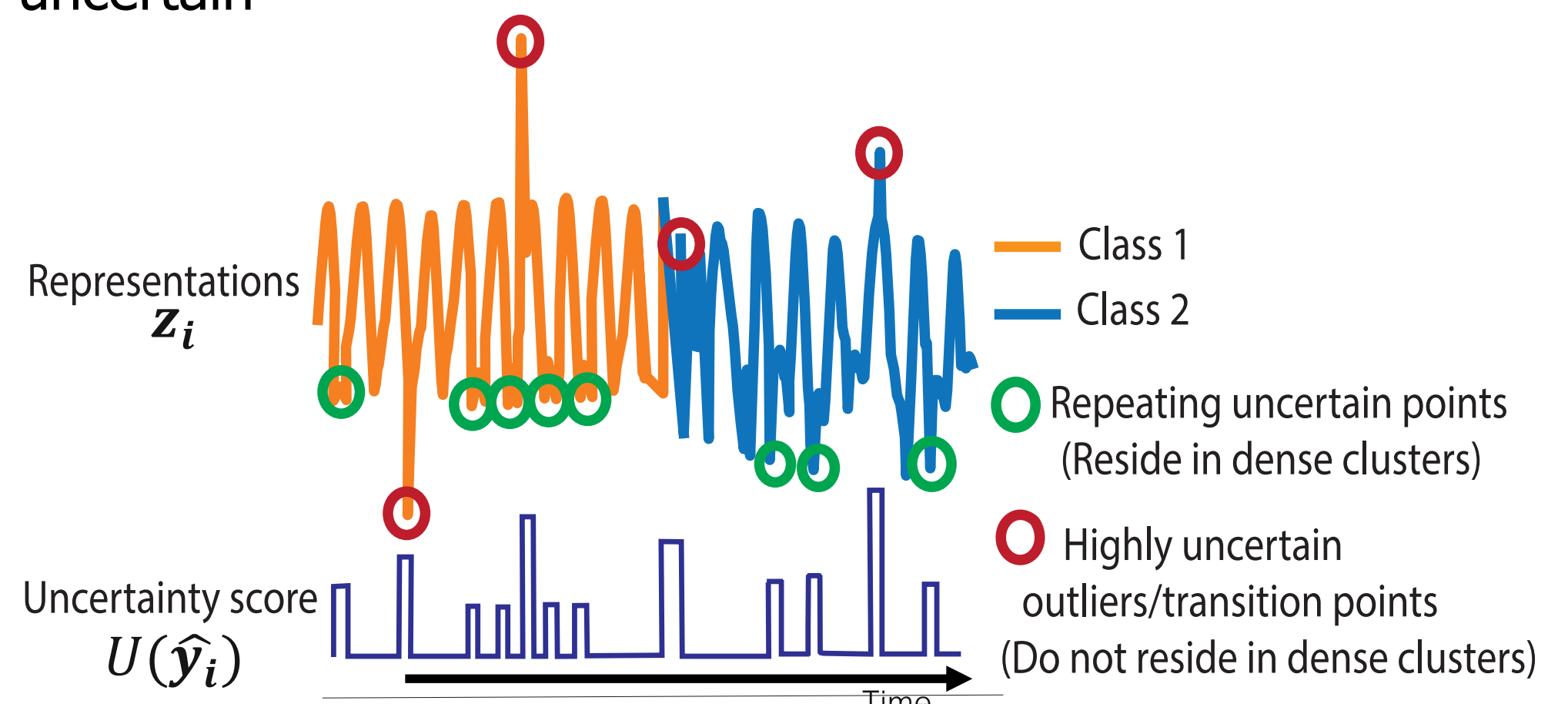
Our method consists of 3 steps:

- 1. Uncertainty quantification:** (Entropy or Margin Sampling) function applied on all softmax probability vectors $y_i, \forall i \in T$
- 2. Clustering:** Representations z_i corresponding to the top K percentile of uncertainty scores $U(\hat{y}_i)$ are clustered into M different clusters through the K -means clustering algorithm.
- 3. Data density:** Out of these M clusters, the top B dense clusters, where B is the sampling budget in an AL round, are selected and the most representative sample for each of these clusters are chosen.

Labels for the chosen samples are obtained and the classifier is then retrained on all the labeled samples. This procedure is repeated until the total labeling budget is met.

Intuition

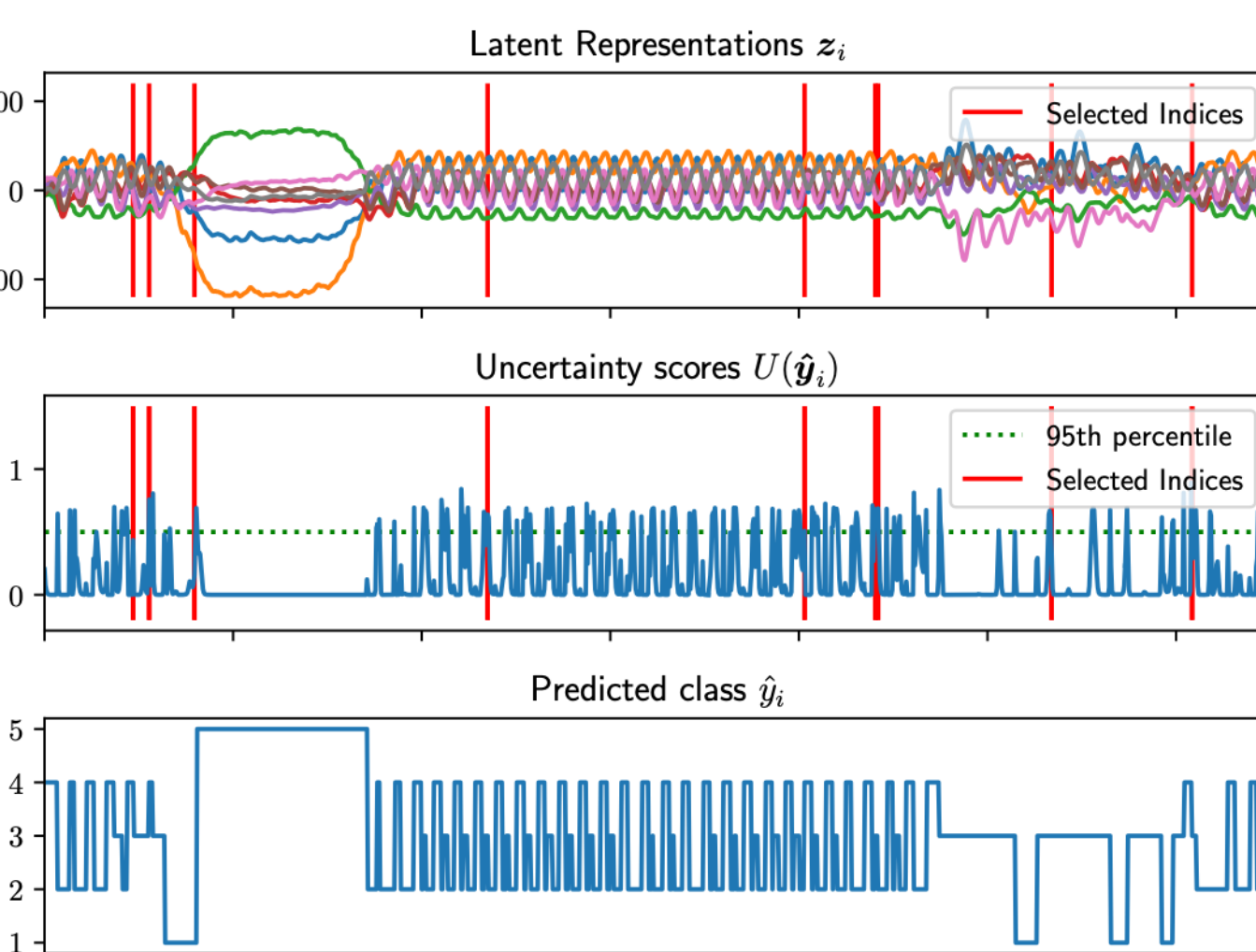
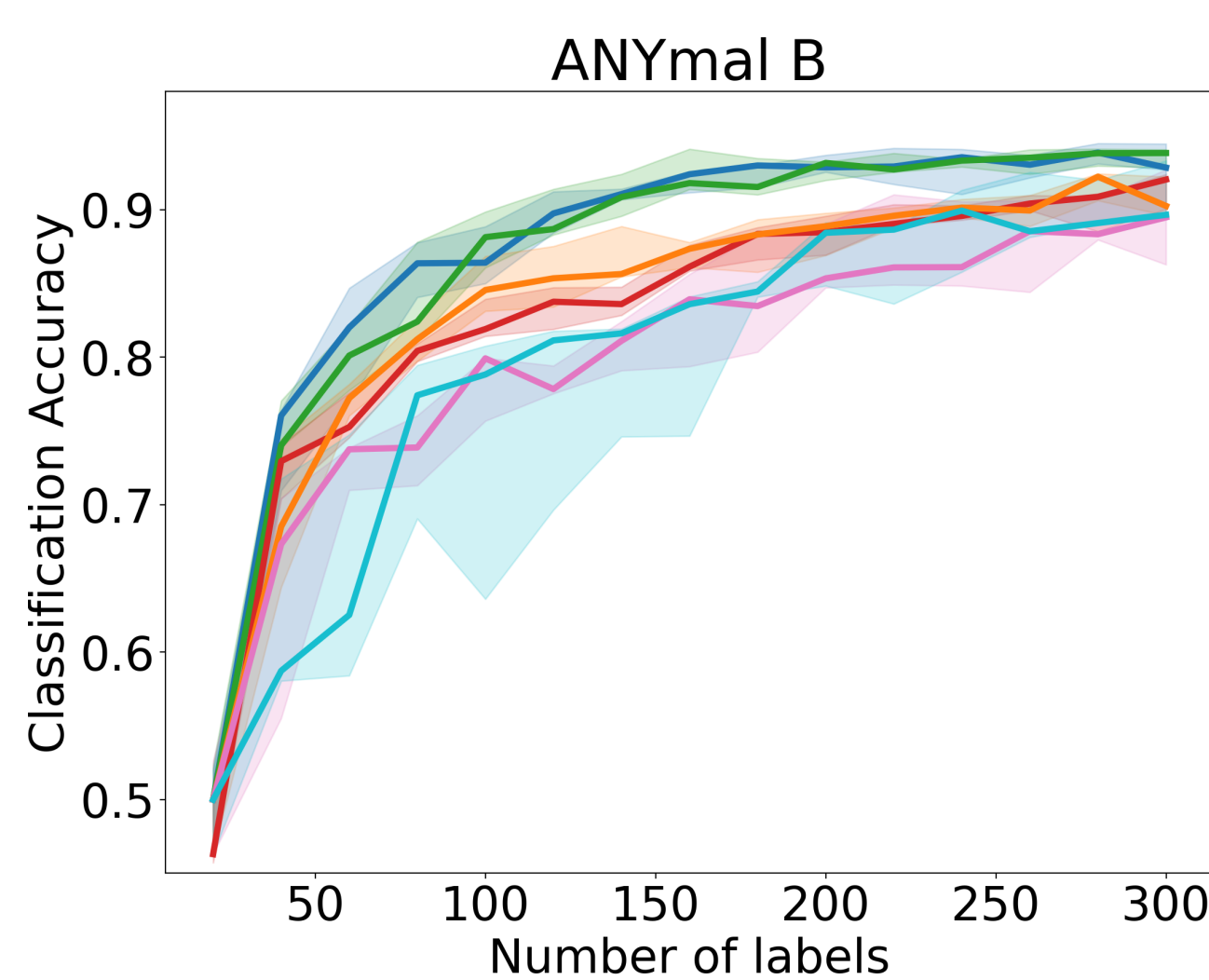
- Representations of periodic time instants are also periodic - clustered together
- Higher density clusters - more frequent uncertain time instants: noisy or class transition points which are inherently uncertain



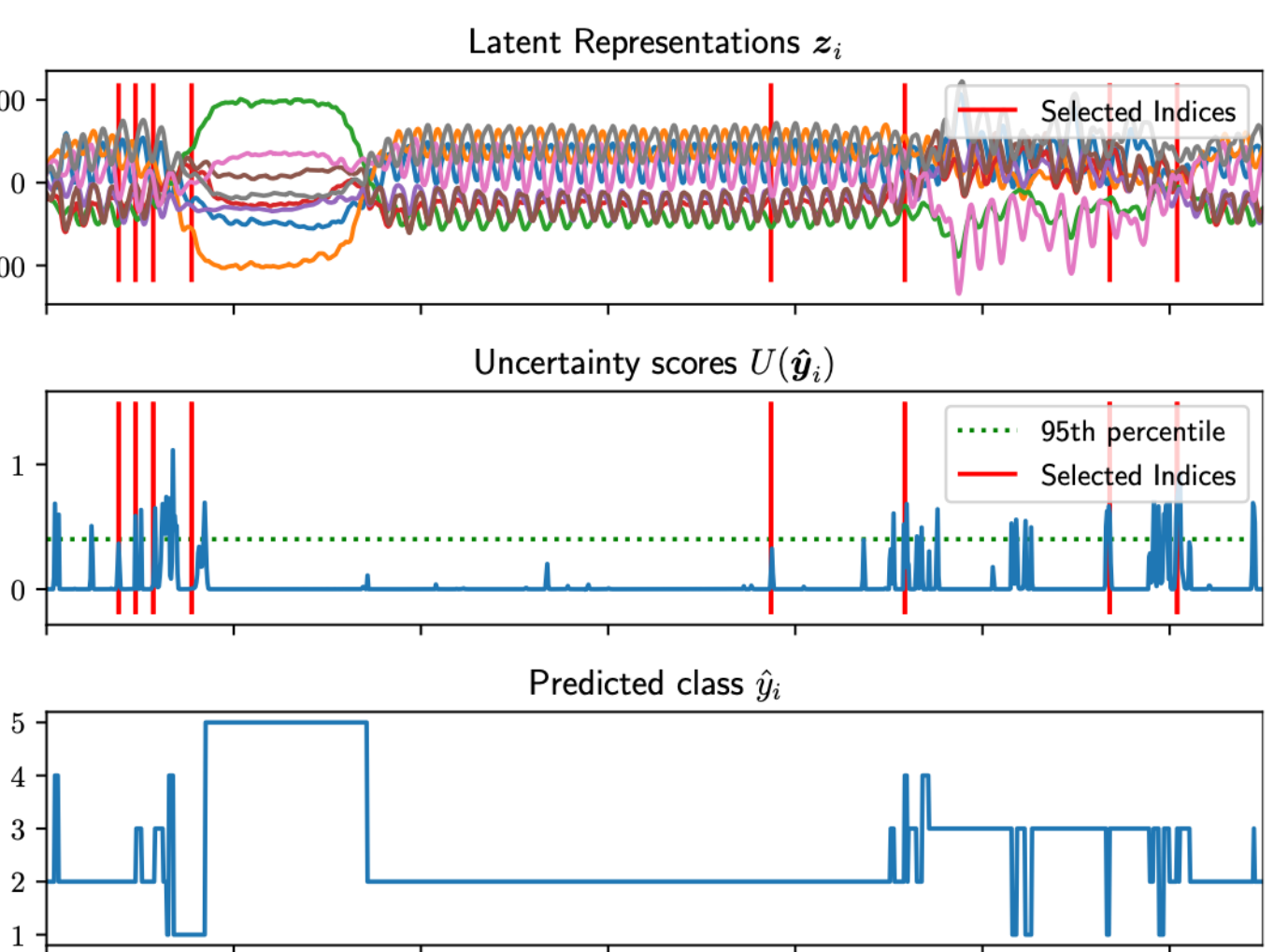
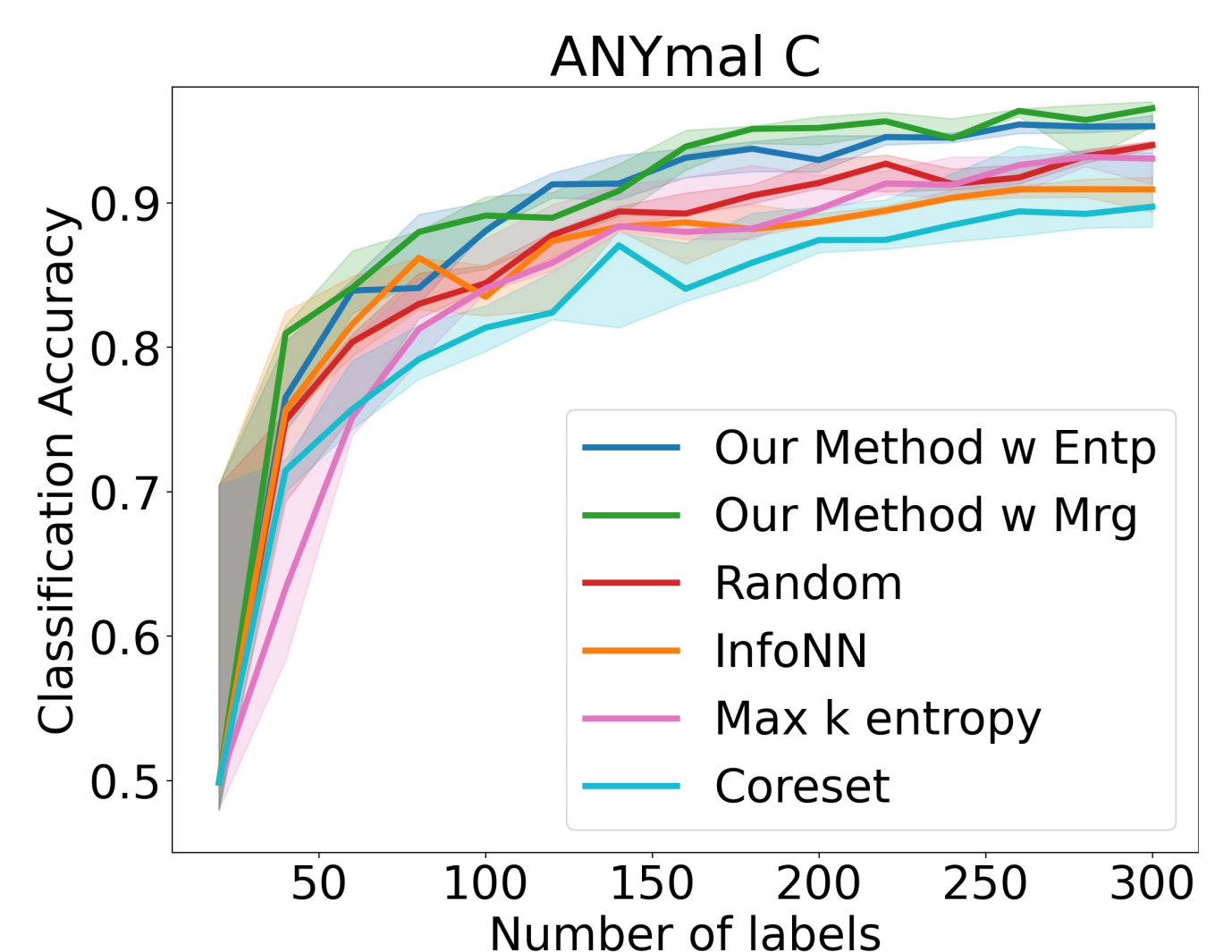
Experiment results

Robot activity dataset

- We use the Isaac gym environment[1] to generate sequences of two different types of quadrupedal robots, ANYmal B and ANYmal C, walking
- Consists of 5 different terrains[2] - walking down a staircase, walking on a flat surface, walking up a staircase, walking down a slope, and walking up a slope.



(B): 52 % accuracy with 20 samples



(C): 75 % accuracy with 40 samples

[1] Liang, J. et al. Gpu-accelerated robotic simulation for distributed reinforcement learning, 2018.

[2] Azabou, M. et al. Learning behavior representations through multi-timescale bootstrapping, 2022.