MI-RNN: Multiple Instance Learning

- Divide into bag of overlapping |length windows (instances).
- Isolate the instances with signature. Relabel these instances and train.
- NP-Hard in general.
- Exploit temporal locality and approximate signature length with MIL/Robust learning techniques in the optimization problem.
- Formulation learns model f as well as starting index i, of the class signature in each data point.

Algorithm:

Step 1: Assign labels \( Z_i = \{x_{i1}, x_{i2}, \ldots, x_{iT}\} \) and map \( x_i \rightarrow Y_i \). 
Step 2: Train classifier \( f \) on this mis-labeled data.
Step 3: Score \( s_i = \sum_{t=1}^{T} Z_i(t) \) and pick argmax \( s_i \). Score \( s_i \).

Step 4: Update Bag \( Z_i \) labels.

Theorem: In \( O(\log n) \) iterations, the true positive set will be recovered exactly, with high prob.

Setting:
- Two classes: \( Z_i^+ \) — negative class instances sampled from a Gaussian with mean \( \mu \).
- \( Z_i^+ \) — positive class instances, lie in a small ball around \( \mu^+ \).
- ISL \( = \log(T) \).
- \( n \geq \exp(\mu^+/\sigma^+)^T \).

Contributions:
- EMI-RNN: exploits temporal structure and shape observations
- USP: a) higher accuracy than baseline RNN architectures
  b) reduce inference time by as much as 72x
  c) Allows deployment on tiny devices like Raspberry Pi0, M4 MCU
- Techniques: multi-instance learning (MIL) + early prediction
- Analysis: recovers provably optimal solution in non-homogeneous MIL settings — first such result for non-homogeneous MIL

EMI-RNN: Early Multi-Instance RNN

- Naive early prediction difficult due to common prefixes
- MI-RNN removes common prefixes making early prediction effective

\[ L(X, y) = \sum_{i=1}^{T} (y_i h_i - y)^2 \]