

What is

MSPRT-TANDEM

Early classification of time series

Is a task to classify sequential data
as **early** and as **accurately**
as possible.

Multi-hypothesis

Sequential

Probability

Ratio

Test

is a nice algorithm for early
multiclass classification.

M

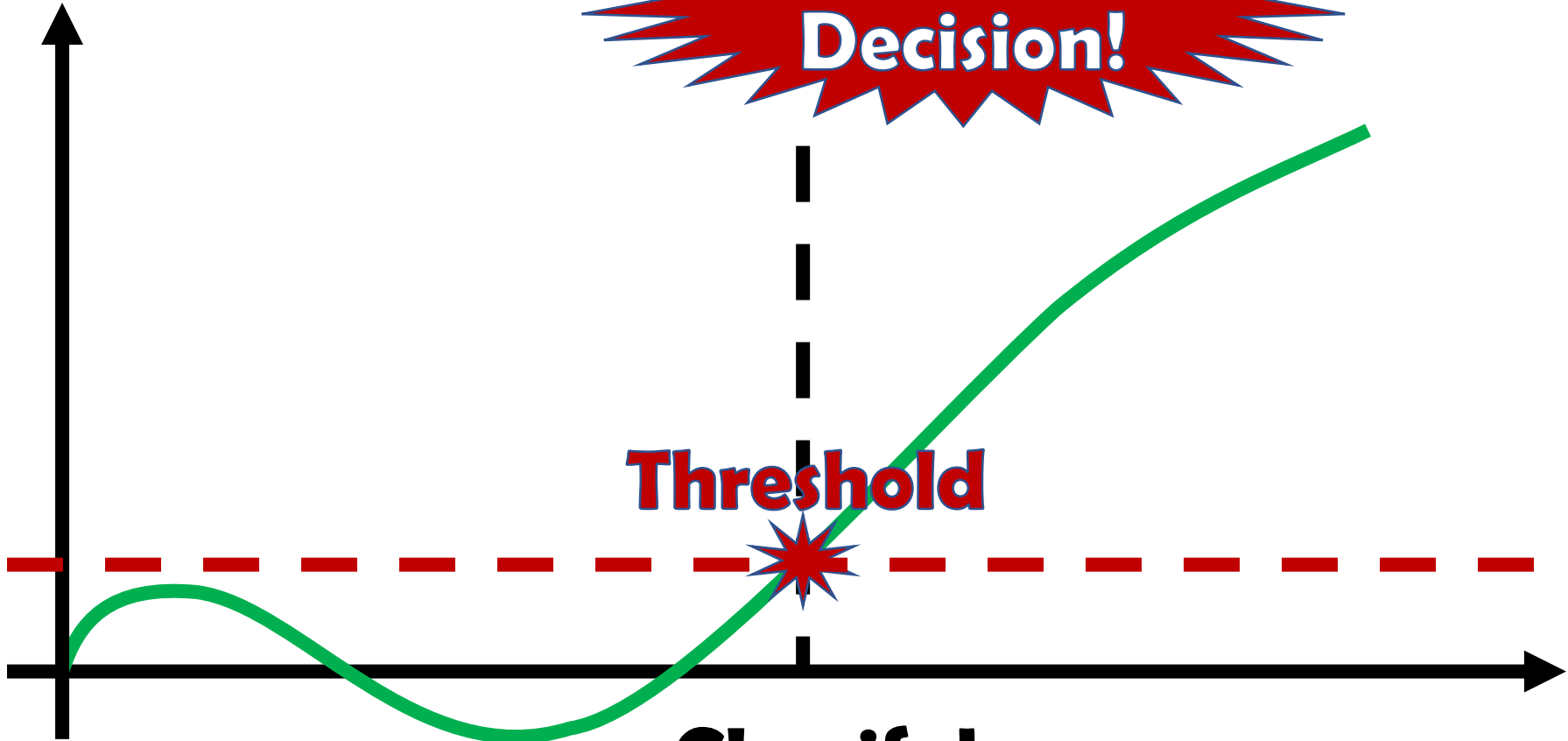
S

P

R

T

Evidence



has a threshold.

Classify!

**Quick
Decision!**

Threshold

Time

M

S

P

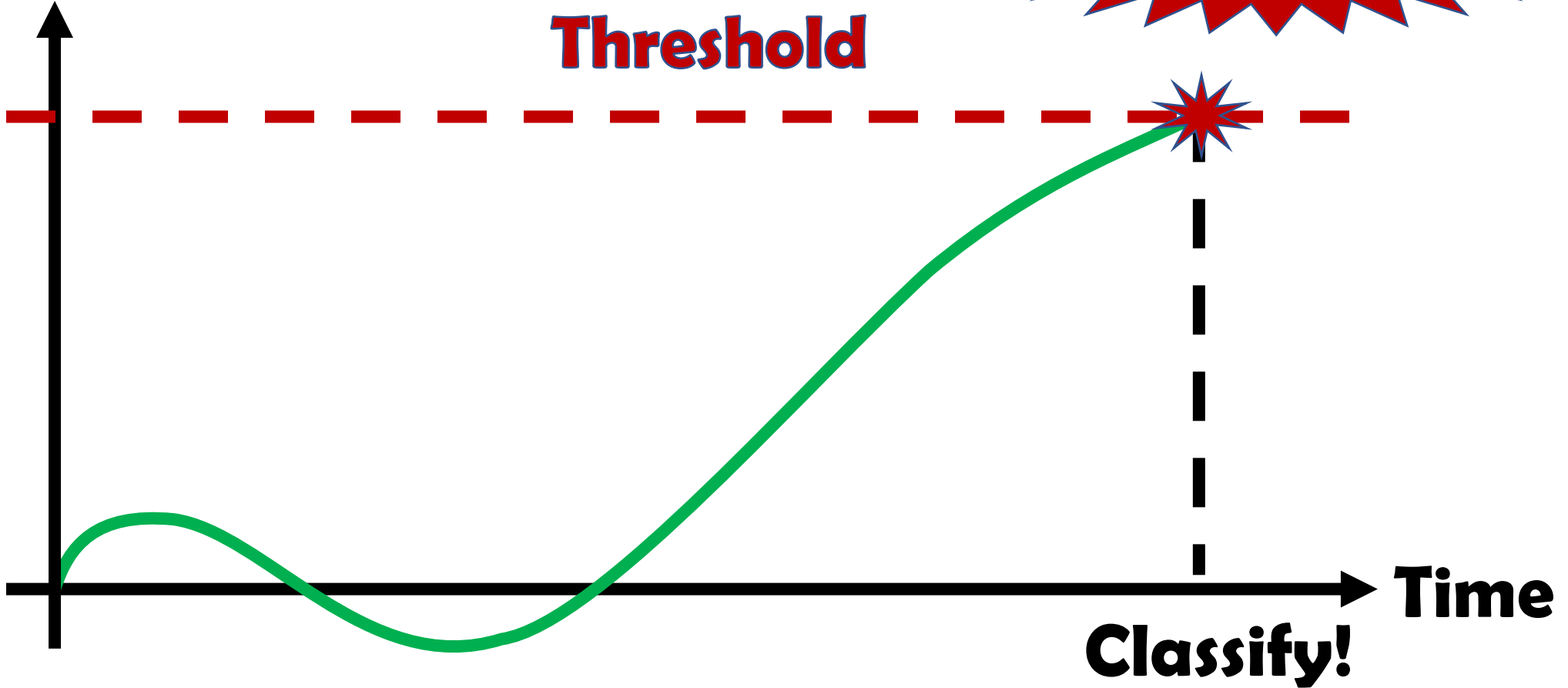
R

T

Evidence

Threshold

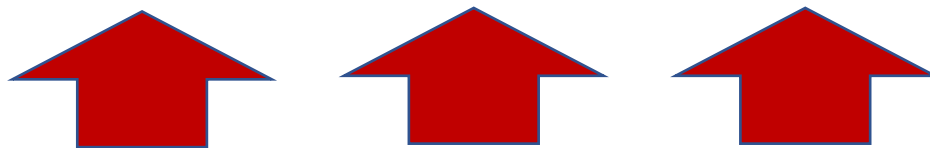
High Accuracy!



has a threshold.

M

Asymptotic optimality

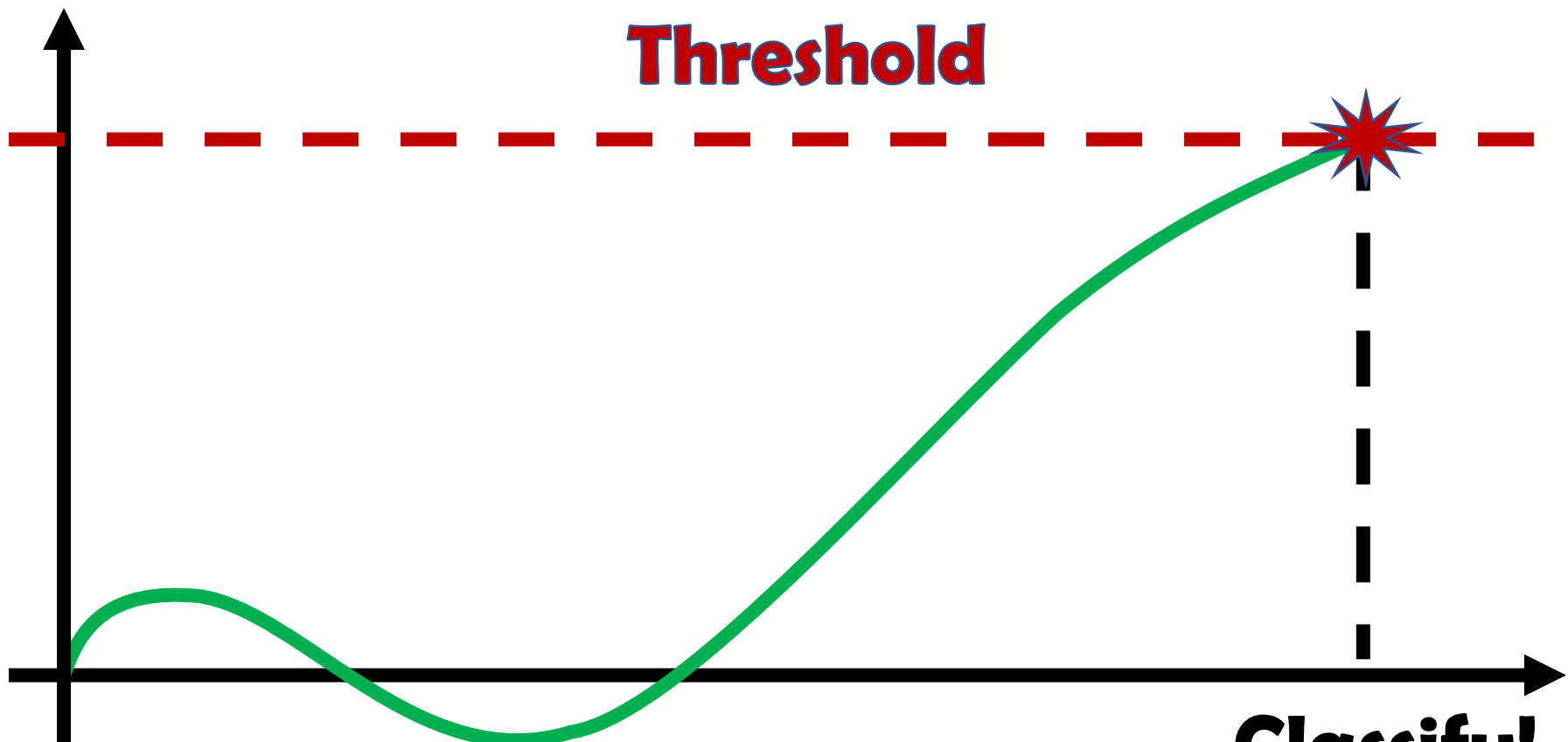


Evidence

S

Threshold

P



R

Classify!

Time

T

is known to be asymptotically optimal.

M

Evidence := Log-Likelihood Ratio Matrix

S

$$\lambda(t) = \left(\log \frac{p(\text{input} = X(t) \mid \text{class} = k)}{p(\text{input} = X(t) \mid \text{class} = l)} \right)_{k,l}$$

P

Prediction = argmax_{rows} min_{columns} λ (Hitting time)

R

T observes LLR matrix.

M

Evidence := Log-Likelihood Ratio Matrix

S

$$\lambda(t) = \left(\log \frac{p(\text{input} = X(t) \mid \text{class} = k)}{p(\text{input} = X(t) \mid \text{class} = l)} \right)_{k,l}$$

P

Prediction = argmax_{rows} min_{columns} λ (Hitting time)

R

T

has a problem.



A faint background illustration of two cartoon rabbits sitting at a desk with a laptop. The rabbit on the left is pink and looking forward, while the rabbit on the right is red and looking towards the laptop. The text is overlaid on this scene.

**Our approach
is
to estimate $\lambda(t)$
from a dataset...**

...but it is difficult...

Multiple density ratios

$$\lambda(t) = \left(\log \frac{p(X(t) | k)}{p(X(t) | l)} \right)_{k,l}$$

Simultaneous optimization

$$= \begin{bmatrix} 0 & \log \frac{p(X(t) | 1)}{p(X(t) | 2)} & \dots & \log \frac{p(X(t) | 1)}{p(X(t) | K-1)} & \log \frac{p(X(t) | 1)}{p(X(t) | K)} \\ \log \frac{p(X(t) | 2)}{p(X(t) | 1)} & \vdots & & \log \frac{p(X(t) | 1)}{p(X(t) | K-1)} & \log \frac{p(X(t) | 2)}{p(X(t) | K)} \\ \vdots & & & 0 & \vdots \\ \log \frac{p(X(t) | K-1)}{p(X(t) | 1)} & \log \frac{p(X(t) | K-1)}{p(X(t) | 2)} & & \vdots & \log \frac{p(X(t) | K-1)}{p(X(t) | K)} \\ \log \frac{p(X(t) | K)}{p(X(t) | 1)} & \log \frac{p(X(t) | K)}{p(X(t) | 2)} & \dots & \log \frac{p(X(t) | K)}{p(X(t) | K-1)} & 0 \end{bmatrix}$$



Our **LSEL** is a solution!!

Minimizing **LSEL**

gives a precise estimate of

$$\lambda(t)$$

LSEL

is a **log-sum-exp**-type loss.

$$L \sim \sum_k \sum_t \sum_i \log \sum_l \exp \left(-\lambda_{kl}(X_i(t)) \right)$$

(classes)(time)(sequences in class k) (columns)

We exploit this structure and prove three theoretical properties, All of which contribute to the performance of the LLR matrix estimation..

LSEL

has three theoretical properties.

Consistency

By minimizing LSEL,
we can get the true λ
in the large training set limit.

**Hard class
weighting**

LSEL gives large gradients
for hard class examples.

**Guess-
aversion**

LSEL returns discriminative
“scores” λ even on class-
imbalanced datasets.

The overall DNN-based model for early multiclass classification

MSPRT + LSEL

= MSPRT-TANDEM

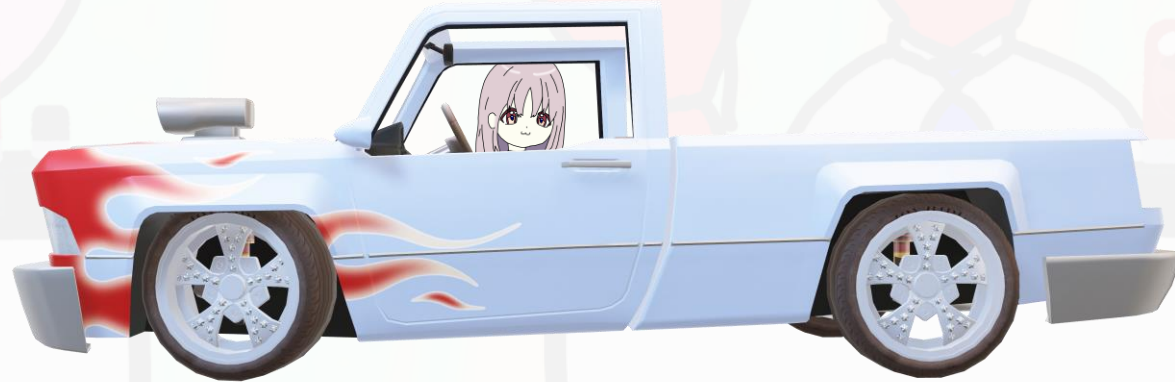
outperforms baseline models statistically significantly.

Potential Applications



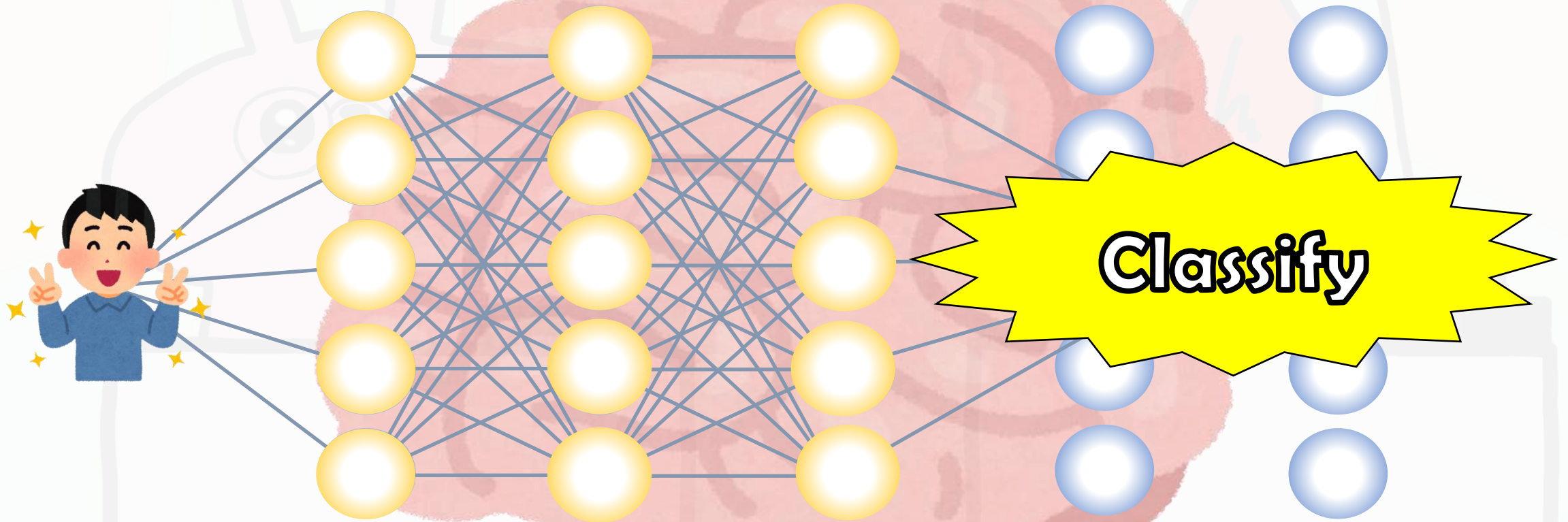
Early detection of patient's deterioration

Potential Applications

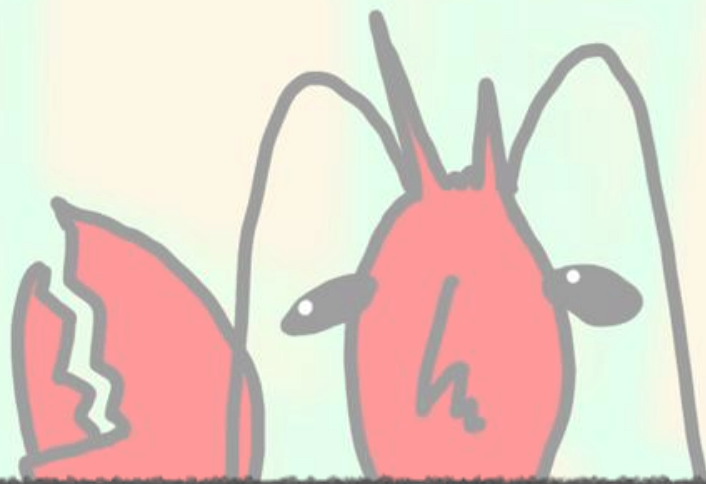


Early action selection for autonomous driving

Potential Applications



Early exit to save computational costs and avoid overfitting in deep learning



MSPRT-TANDEM



Title

The Power of **Log-Sum-Exp**:
Sequential Density Ratio Matrix Estimation
for Speed-Accuracy Optimization

Authors

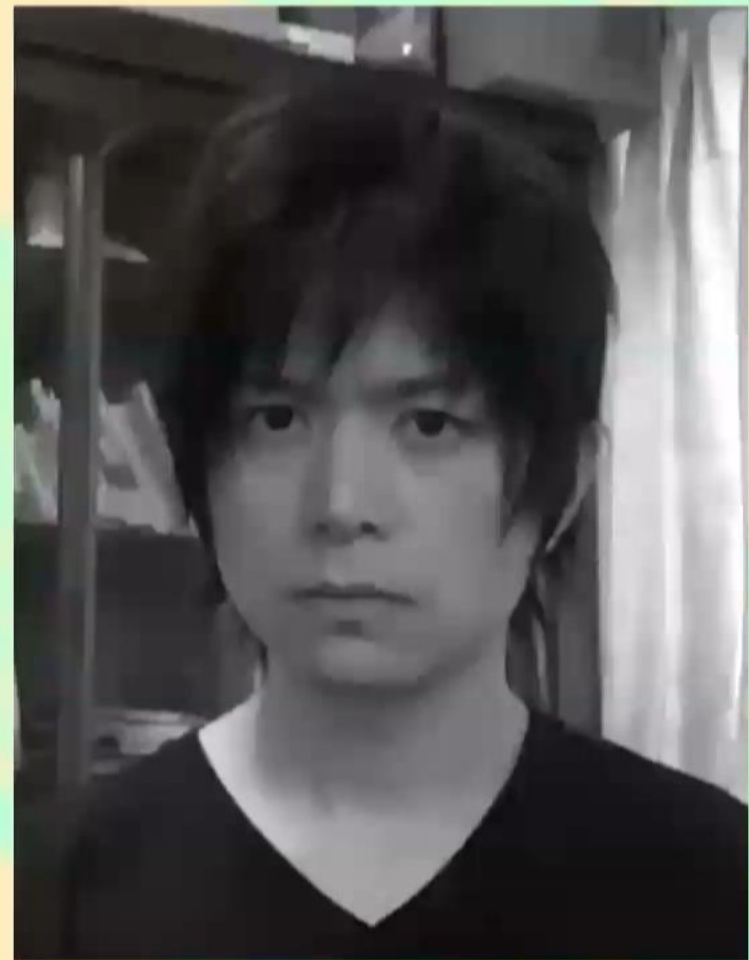
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Taiki Miyagawa

An ordinary rabbit.

Twitter [@kanaheinousagi](https://twitter.com/kanaheinousagi)



Akinori F. Ebihara

**A neuroscience Ph.D. working in the field of
machine learning/computer vision.**

An orchid enthusiast. A father of a son.

Twitter [@non_iid](https://twitter.com/non_iid)

Summary

- The **MSPRT** is known to be **asymptotically optimal**, but it requires the true LLR of the input, which limits its real-world applications.
- We relax this critical requirement via **Density Ratio Matrix Estimation (DRME)**.
- We propose a loss function, the **LSEL**, for DRME.
- We prove that the LSEL is **consistent, weighs hard classes, and is guess-averse**.
- Our experiment shows that **MSPRT+LSEL = MSPRT-TANDEM** outperforms other baseline models on a large-scale action recognition datasets (UCF101 and HMDB51).
- **MSPRT-TANDEM opens up possibilities for the MSPRT in wide variety of tasks.**