MACHINE LEARNING FOR HEALTH

Deep Learning II: Transformers and the Pulse of Data

Attention, time series, and physiological signals in clinical settings

TECHNICAL HANDOUT · SESSION 08

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Academic teaching material based exclusively on the PDFs available in the project

Table of Contents

Introduction

Physiological signals are sequences sampled by devices and are subject to noise, artifacts, differing frequencies, and changes in context. The computational challenge is to preserve temporality and relate local patterns, long-range dependencies, and clinical state. [1]

This session compares recurrent networks and Transformers and discusses how these architectures can transform time series into representations and predictions while maintaining attention to synchronization, alarms, and explanations. [1]

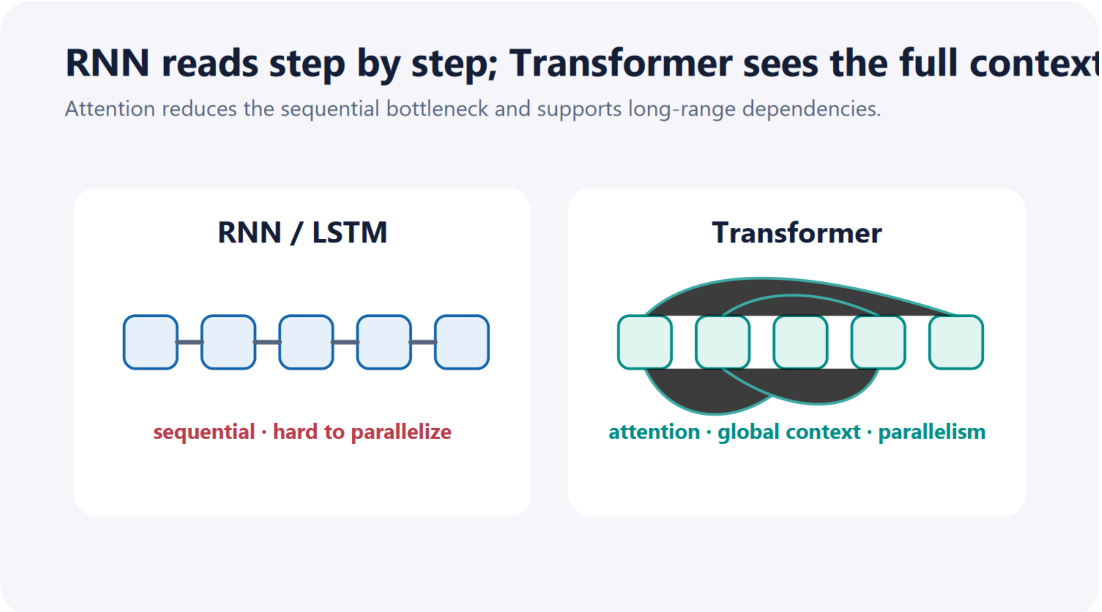

Figure 1 — Recurrent processing and parallel attention. Source: original illustration based on [2].

1. Signal, time, and context

Monitoring systems acquire ECG, blood pressure, oximetry, and other signals, process them, and present them in an integrated way. Artifacts, connection losses, differences in sampling, and alarm limits affect the information that reaches the algorithm [1].

The input to a temporal model may be a multivariate window; its output may be a class, event, risk, or predicted sequence. Defining the horizon separates detection in the present from prediction of a future event [2].

KEY CONCEPT
Monitoring systems acquire ECG, blood pressure, oximetry, and other signals, process them, and present them in an integrated way.

2. Recurrence and memory

RNNs update a state as they traverse a sequence. LSTMs and GRUs introduce mechanisms that favor retaining and forgetting information, addressing difficulties with long-range dependencies. Sequential processing, however, limits parallelism and can make distant relationships difficult to learn [2].

3. Attention and Transformers

Transformers use attention units to relate positions in a sequence. Instead of relying only on a state propagated step by step, each position can weight other relevant positions. The representation must preserve order information because attention alone does not provide temporality [2].

For signals, segments or samples are transformed into representations, combined with position information, and processed by attention blocks. The output may be aggregated for classification or preserved over time for detection and prediction [2].

4. Multimodality, alarms, and explanation

Signals with different frequencies require alignment and explicit handling of gaps. In the ICU, a prediction should be compared with conventional thresholds and integrated with response capacity. Excessive alarms reduce effectiveness and can lead to high override rates [1].

A temporal explanation may indicate segments, channels, and context associated with the result, but attention weights should not automatically be treated as causal explanations. Evaluation should include stability, usefulness to the user, and behavior under noise or artifacts [3].

SOURCE LIMITATION
The local PDFs provide conceptual support for Transformers and signals but do not reproduce every architecture and study indicated in the slides.

Session summary

Signal, time, and context: monitoring systems acquire ecg, blood pressure, oximetry, and other signals, process them, and present them in an integrated way.
Recurrence and memory: rnns update a state as they traverse a sequence.
Attention and Transformers: transformers use attention units to relate positions in a sequence.
Multimodality, alarms, and explanation: signals with different frequencies require alignment and explicit handling of gaps.

References

[1] Herasevich, V. et al. Patient Monitoring Systems. In: Biomedical Informatics. Springer, 2021. External link

Local file: pdfs/2-Biomedical Informatics/XXI-Patient Monitoring Systems.pdf · PDF pages used: 1, 4, 10, 13, 14.

[2] Bellazzi, R.; Dagliati, A.; Nicora, G. Predicting Medical Outcomes. In: Intelligent Systems in Medicine and Health. Springer, 2022. External link

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[3] Li, R. C. et al. Explainability in Medical AI. In: Intelligent Systems in Medicine and Health. Springer, 2022. External link

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