From Indicators to Insights: Diversity-Optimized for Medical Series-Text Decoding via LLMs

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https://github.com/jinxyBJTU/InDiGO

Background and Motivations

Background

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From Pattern Recognition to Physiological Understanding

Regular Time Series	vs.	Medical Time Series
Physically or mechanically generated (e.g.,weather,traffic)	Nature of signals	Biophysiological and multi-source (e.g., EEG, ECG, EMG)
Stable statistical patterns, often stationary	Data consistency	High inter-subject variability, non-stationary dynamics
Approximate prediction acceptable	Error tolerance	Misinterpretation may lead to clinical risk

Medical time series transform pattern recognition into **knowledge-driven interpretation** — where data must be understood within its physiological context.

Motivations

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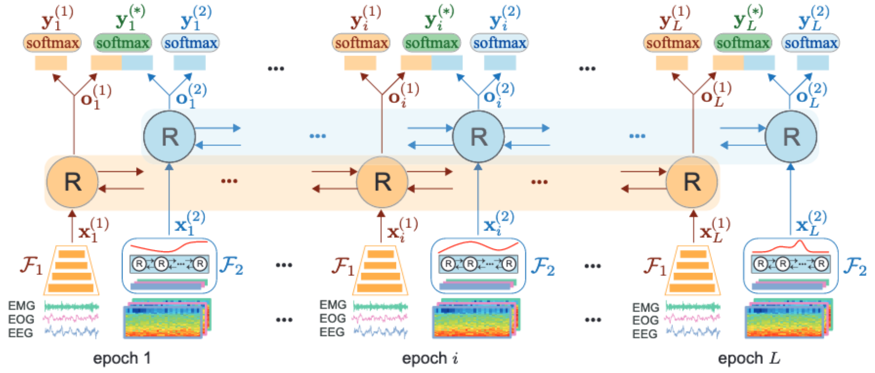
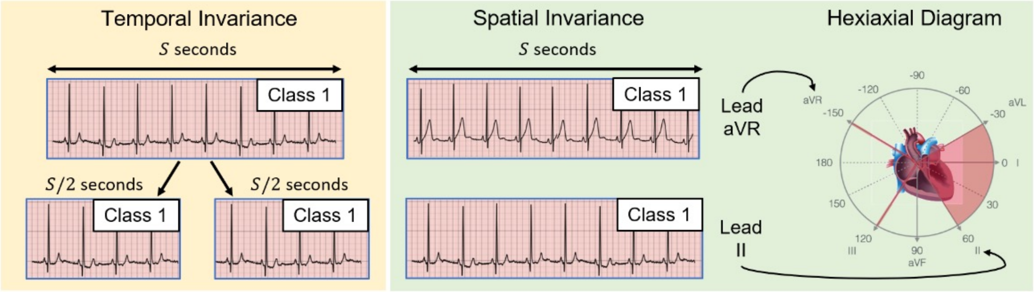
Early knowledge integration in medical modeling:

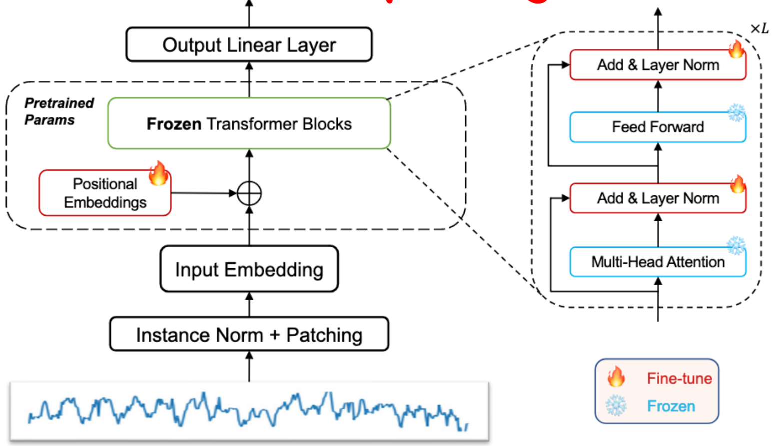


Task-specific module design

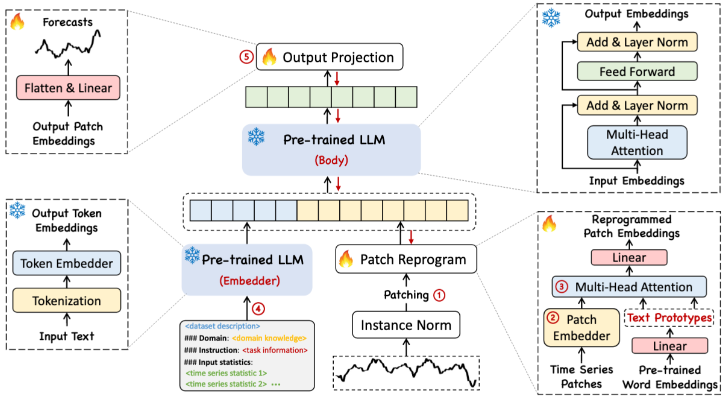


Task-agnostic loss design

LLMs have become a new paradigm due to their efficient ability to transform knowledge



Implicit knowledge modeling



Explicit knowledge encoding

Motivations

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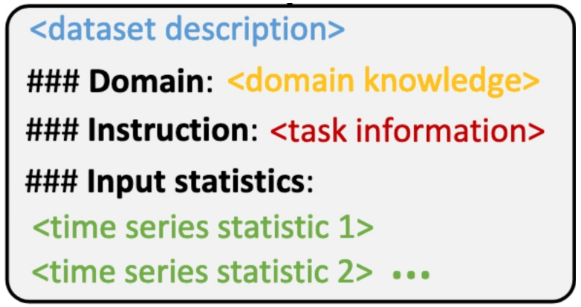
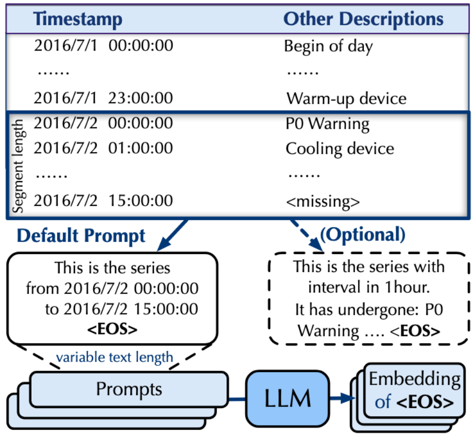
Limited inspiration for decision-making

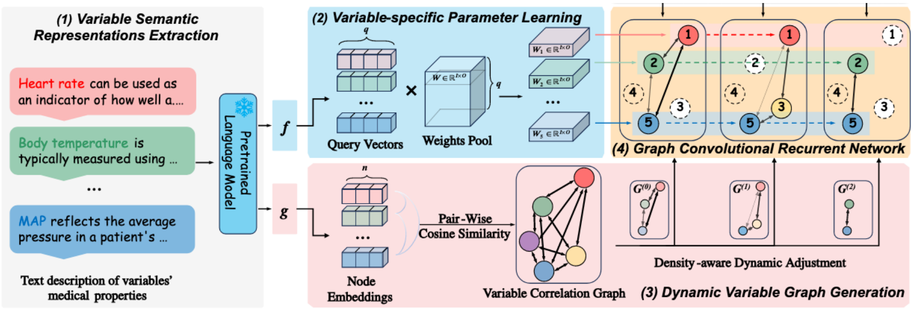


(a) dataset descriptions and sample statistics



(b) timestamp information

Gap



(c) time-varying inter-variable dependencies

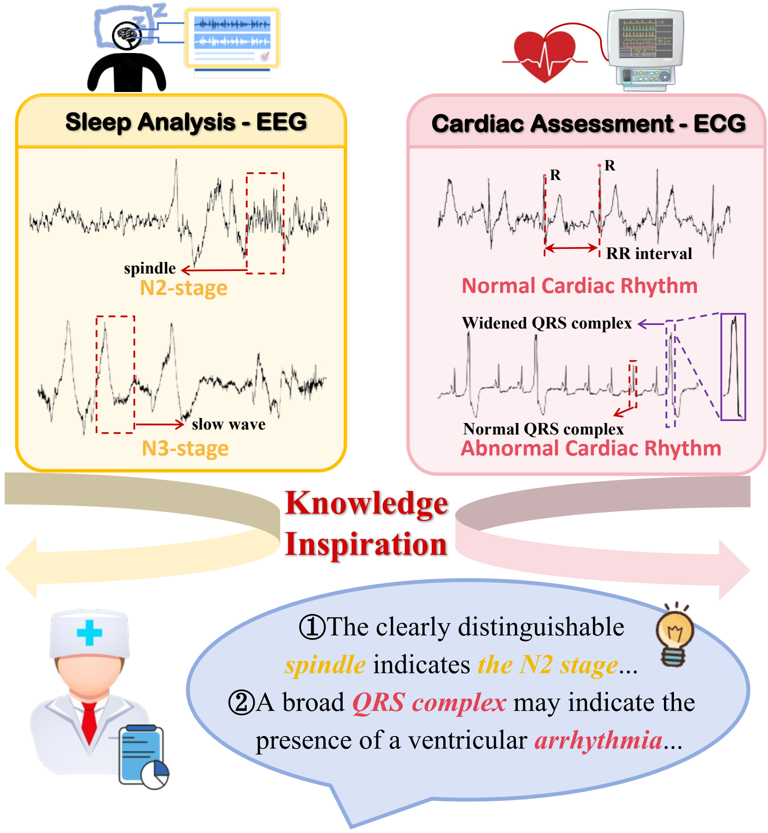


Figure 1: Task-relevant indicators provide critical cues for physiological state interpretation in sleep analysis and cardiac assessment

Motivations

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Chanllenges

- **What kinds of promptable knowledge are most effective for decoding medical time series?**
  - Existing prompts lack task-specific, discriminative cues that experts actually rely on. The challenge is to identify what type of knowledge truly drives physiological interpretation.
- **How to robustly integrate time series and suboptimal text prompts?**
  - Text prompts may be incomplete or inaccurate.
  - A robust model must still align and learn meaningful cross-modal representations even when the textual guidance is noisy or partially wrong.

InDiGO —— designed to integrate indicator-guided prompts and optimize their diversity and alignment through an evolutionary learning process.

Method

Method

InDIGO — Indicator-informed Diversity-Guided Optimization

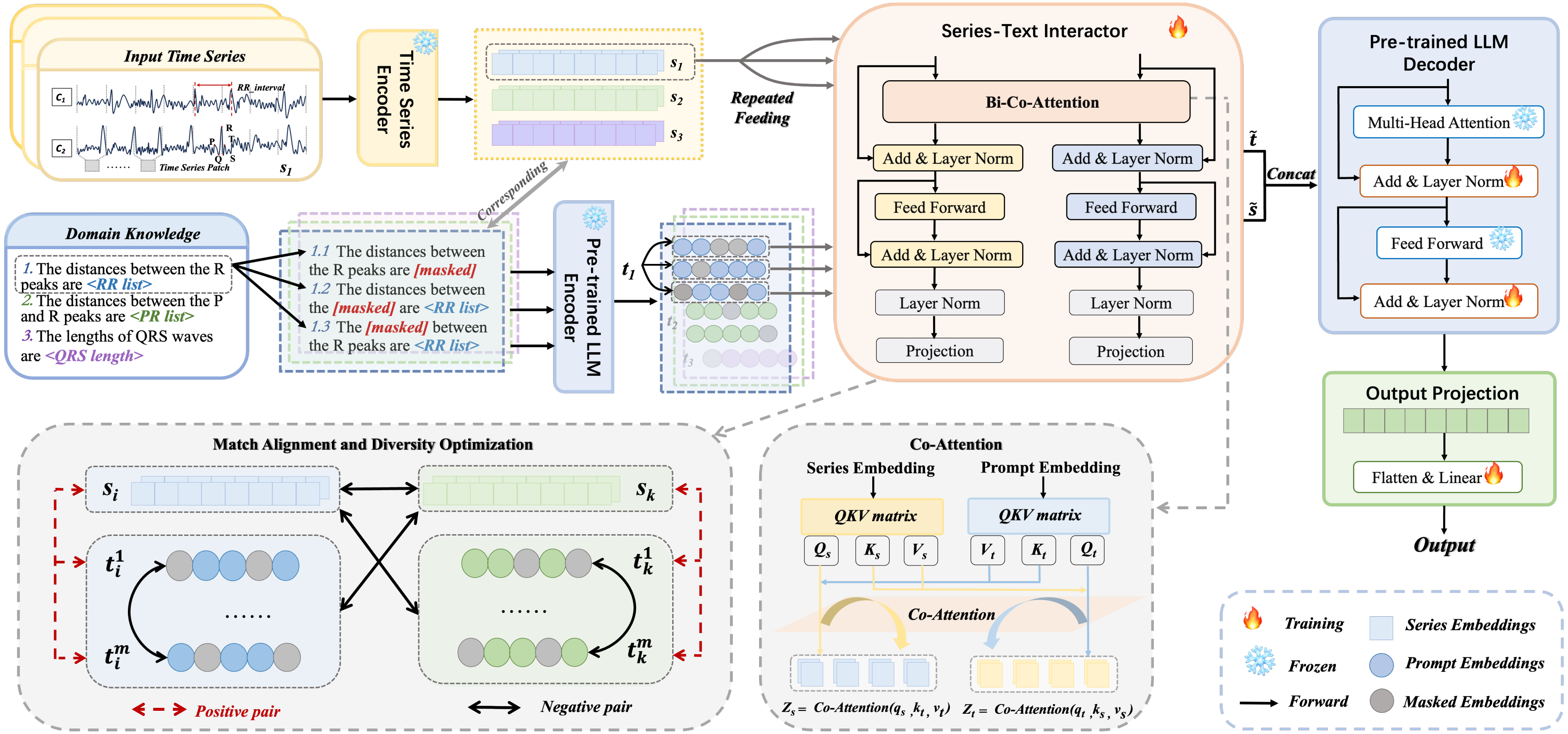

Figure 1: Overview of InDiGO. Given medical time series and initial texts, we apply mask-based importance sampling and pre-trained encoders to extract features. A series-text interactor captures relevance, followed by alignment and diversity optimization to identify the optimal combination.

Method

Step 1: Indicator-Guided Prompt Prototype Construction

LLM predicts the target conditioned on both the series and a text prompt :

$$P_{\text{LLM}}(Y) = \mathbb{E}_{(s,t)\sim P(s,t)}\left[P_{\text{LLM}}(Y|s,t)\right] \approx \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}_{t\sim P(t|s_i)}\left[P_{\text{LLM}}(Y|s_i,t)\right]$$

In practice, we approximate the whole text distribution with a single suboptimal text → this introduces bias

$$P_{\text{LLM}}(Y) = \mathbb{E}_{(s,t)\sim P(s,t)}\left[P_{\text{LLM}}(Y|s,t)\right] \approx \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}_{t\sim P(t|s_i)}\left[P_{\text{LLM}}(Y|s_i,t)\right]$$

$$\text{Bias}(\hat{\mathcal{M}}) = \mathbb{E}[P_{LLM}(y_i|s_i,t)P(t|s_i)] - \int P_{LLM}(y_i|s_i,t)P(t|s_i)dt$$

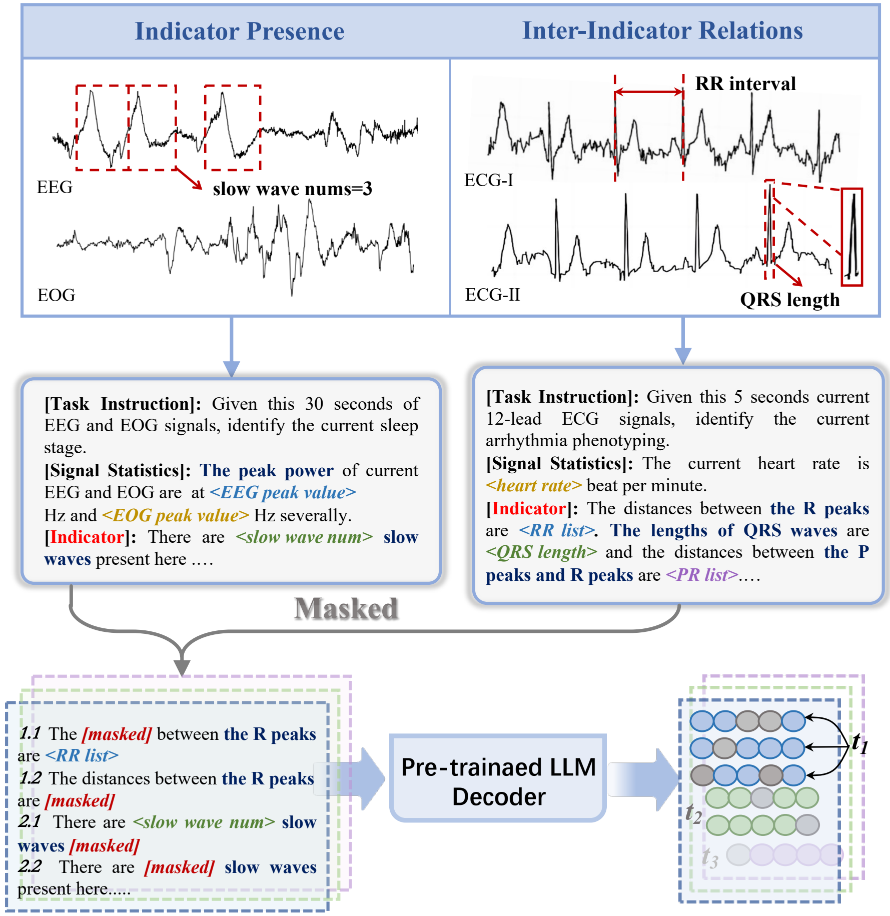

Figure 3: Scene-specific indicator prompting via semi-automated extraction.

Method

Step 2: Masked Monte Carlo Importance Sampling

Marginal likelihood: $$\hat{\mathcal{M}} = \int P_{\text{LLM}}(y_i|s_i,t)q(t|t_i^0)\frac{P(t|s_i)}{q(t|t_i^0)}dt \approx \frac{1}{m}\sum_{j=1}^{m} P_{\text{LLM}}(y_i|s_i,t_i^j)\frac{P(t_i^j|s_i)}{q(t_i^j|t_i^0)}$$

Optimal Text Prompt: $$t_i^* = \underset{t_i}{\text{argmax}}[\log P_{\text{LLM}}(y_i|s_i,t_i) + \log P(t_i|s_i) - \log q(t_i|t_i^0)]$$

Random Masking Operation: $$\mathcal{D}^{t_i} = \{t_i^j|t_i^{j,1}, t_i^{j,2}, \ldots, t_i^{j,L_{t_i}}; j = 1, \ldots, m\}$$

Step 3: Match Alignment + Diversity Optimization

Series-Text Interaction: $$(\mathbf{z}_s, \mathbf{z}_t) = \text{BiCoAttn}(\mathbf{s}, \mathbf{t}) = \left(\text{softmax}\left(\frac{\mathbf{q}_s\mathbf{k}_t^\top}{\sqrt{d}}\right)\mathbf{v}_t,\ \text{softmax}\left(\frac{\mathbf{q}_t\mathbf{k}_s^\top}{\sqrt{d}}\right)\mathbf{v}_s\right)$$

Alignment and Diversity Optimization: $$\mathcal{L}_{\text{objective}} = \mathbb{E}_{t_i^j \sim q(t|t_i^0)}[-\log P(s_i|t_i^j)] - H(q(t|t_i^0))$$

Results

Results

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Methods	Sleep-EDF-20			Sleep-EDF-78		
	Acc.	Macro F1	Kappa	Acc.	Macro F1	Kappa
TF-C [48]	55.42 ±1.39	26.04 ±0.21	30.74 ±1.52	53.90 ±4.03	26.00 ±2.09	29.32 ±6.43
SimMTM [7]	66.91 ±1.89	53.21 ±1.95	53.25 ±2.02	63.06 ±2.67	57.07 ±2.13	53.07 ±3.42
OneFitsAll [49]	72.60 ±1.51	61.61 ±5.80	61.81 ±3.50	68.50 ±2.19	54.24 ±1.96	55.21 ±3.07
Time-LLM [12]	80.31 ±2.63	71.64 ±3.02	70.22 ±2.84	78.08 ±2.96	66.09 ±3.25	68.04 ±3.14
KEDGN [24]	74.89 ±3.86	64.29 ±3.36	64.90 ±5.46	70.34 ±1.85	58.59 ±2.74	57.47 ±2.56
MiniRocket [5]	81.60 ±1.55	72.82 ±2.01	72.79 ±1.96	78.36 ±1.93	70.18 ±2.35	69.46 ±2.46
BIOT [45]	81.86 ±4.41	75.29 ±4.47	75.14 ±6.00	77.15 ±3.04	69.36 ±4.13	68.26 ±4.36
TinySleepNet [38]	83.64 ±2.31	77.54 ±2.55	77.63 ±2.29	83.49 ±2.24	76.64 ±2.61	76.41 ±2.59
XSleepNet [32]	80.93 ±2.34	76.71 ±2.59	74.31 ±2.32	81.83 ±2.30	75.28 ±2.66	75.44 ±2.37
L-SeqSleepNet [33]	82.90 ±2.12	74.90 ±2.22	76.47 ±2.24	80.84 ±2.18	72.67 ±2.38	74.94 ±2.51
SleepHGNN [10]	81.15 ±1.96	72.88 ±2.17	73.35 ±2.16	77.35 ±2.13	69.56 ±2.39	68.65 ±2.41
SleepKD [21]	82.44 ±2.40	74.11 ±2.72	76.87 ±2.63	80.19 ±2.85	72.65 ±2.84	74.86 ±2.93
SleepDG [42]	81.92 ±2.27	74.74 ±2.53	76.43 ±2.47	79.95 ±2.42	72.21 ±2.59	74.16 ±2.68
Brant-X [47]	84.58 ±1.98	77.63 ±2.13	79.29 ±2.18	82.84 ±2.21	77.04 ±2.30	76.67 ±2.49
InDiGO	**89.04** ±1.80	**80.53** ±1.77	**84.91** ±2.51	**86.79** ±1.90	**81.12** ±1.88	**81.60** ±2.89

Table 1: 5-fold cross-validated average results for sleep stage classification

Results

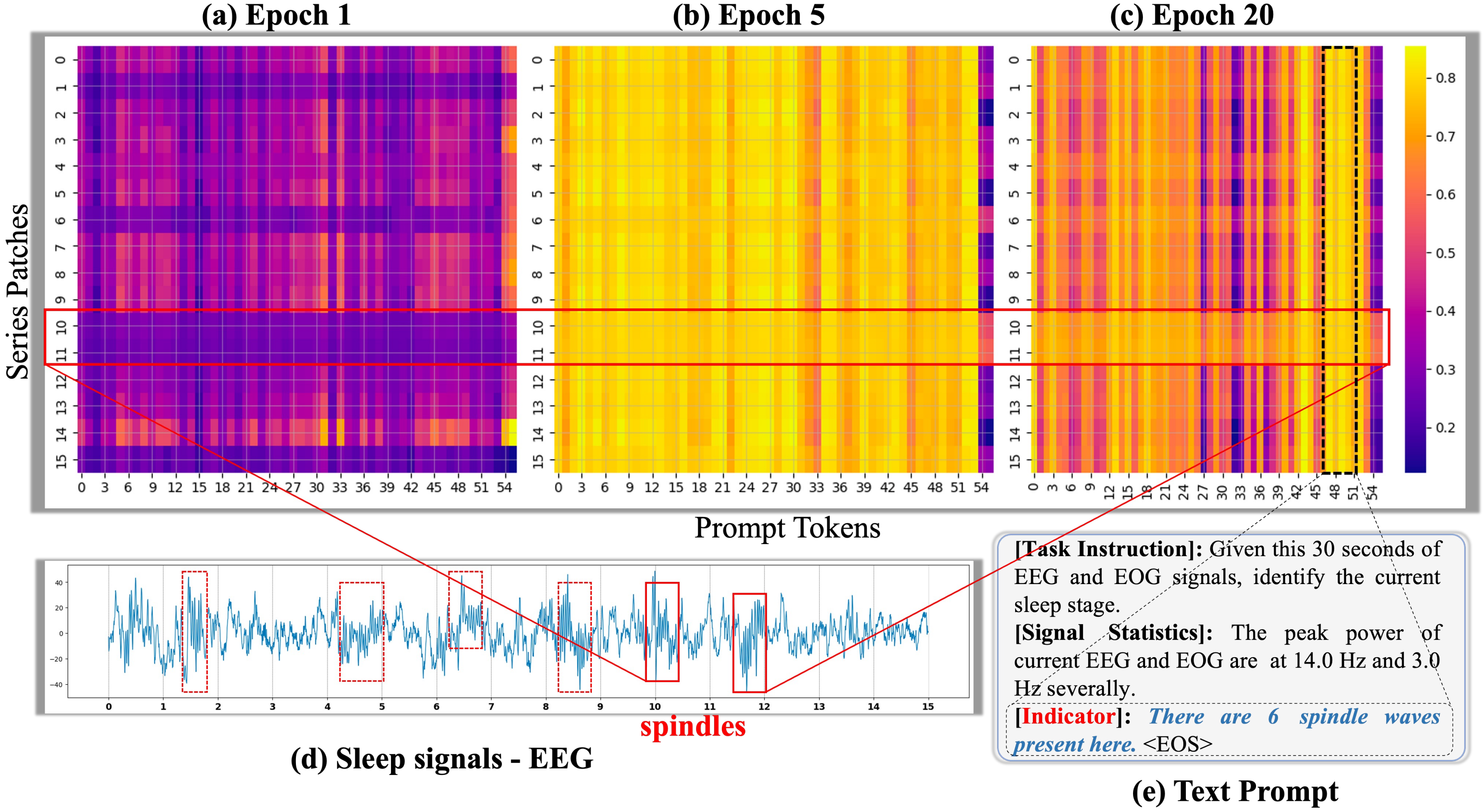

Figure 6: A showcase of series-text correlation with network training. (a)-(c) represent the co-attention scores of the series-text pair, (d) and (e) represent the series and text samples.

Thank you for your listening !

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