In this study, we analyze the rain-related information available from commercial microwave links (CMLs) under different sampling protocols. A Transformer-based model is employed as an analysis tool and is adapted to effectively extract rainfall information from the CML measurements.

Transformer interpretability analysis is particularly important in meteorological and public-infrastructure applications. Specifically, we use raw self-attention visualization, which is a widely adopted and intuitive approach for understanding Transformer behavior.

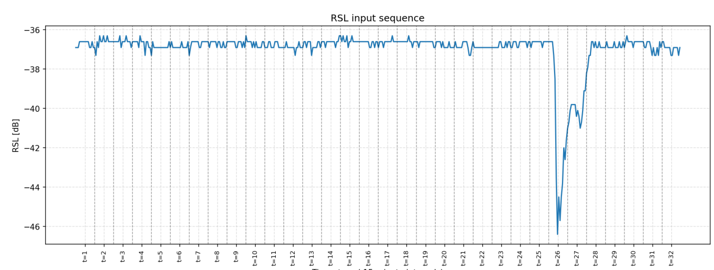
The core building block of a Transformer is the self-attention mechanism, which assigns a pairwise attention weight between every two tokens. These attention weights involves the computetion of queries and keys, computed as softmax $\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)$, are commonly interpreted as relevance scores indicating how strongly each token attends to others.

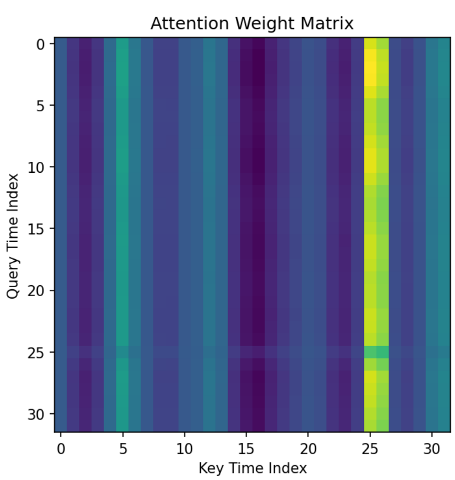
In our setting, a token corresponds to a 15-minute time window, whose internal dimensionality depends on the sampling protocol (e.g., min-max or instantaneous sampling). Accordingly, the Transformer input has the form [batch size, T, input dimesnios] , where T denotes the number of consecutive 15-minute intervals. For a given link (batch element), each attention matrix is therefore of size $T \times T$, representing temporal dependencies between time windows. Such matrices are produced for each encoder layer and each attention head.

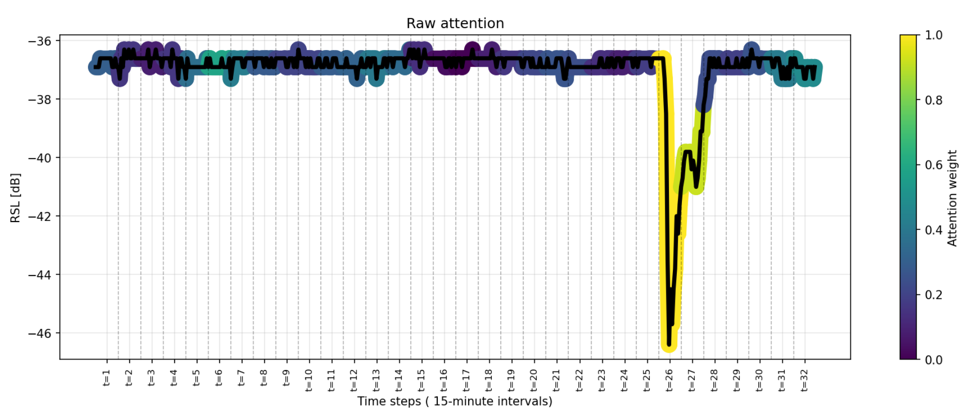
To provide an intuitive interpretation, we select a representative link from the validation set and a time segment ($T = 32$, corresponding to 8 hours) containing rain events. Without loss of generality, we present results for an instantaneous sampling interval of one minute. We visualize how attention weights align with the received signal level (RSL) time series, highlighting which temporal regions the model emphasizes during rainfall events.

Representative examples of the raw self-attention visualization described above are shown below. corresponding to individual attention heads selected for illustrative purposes.

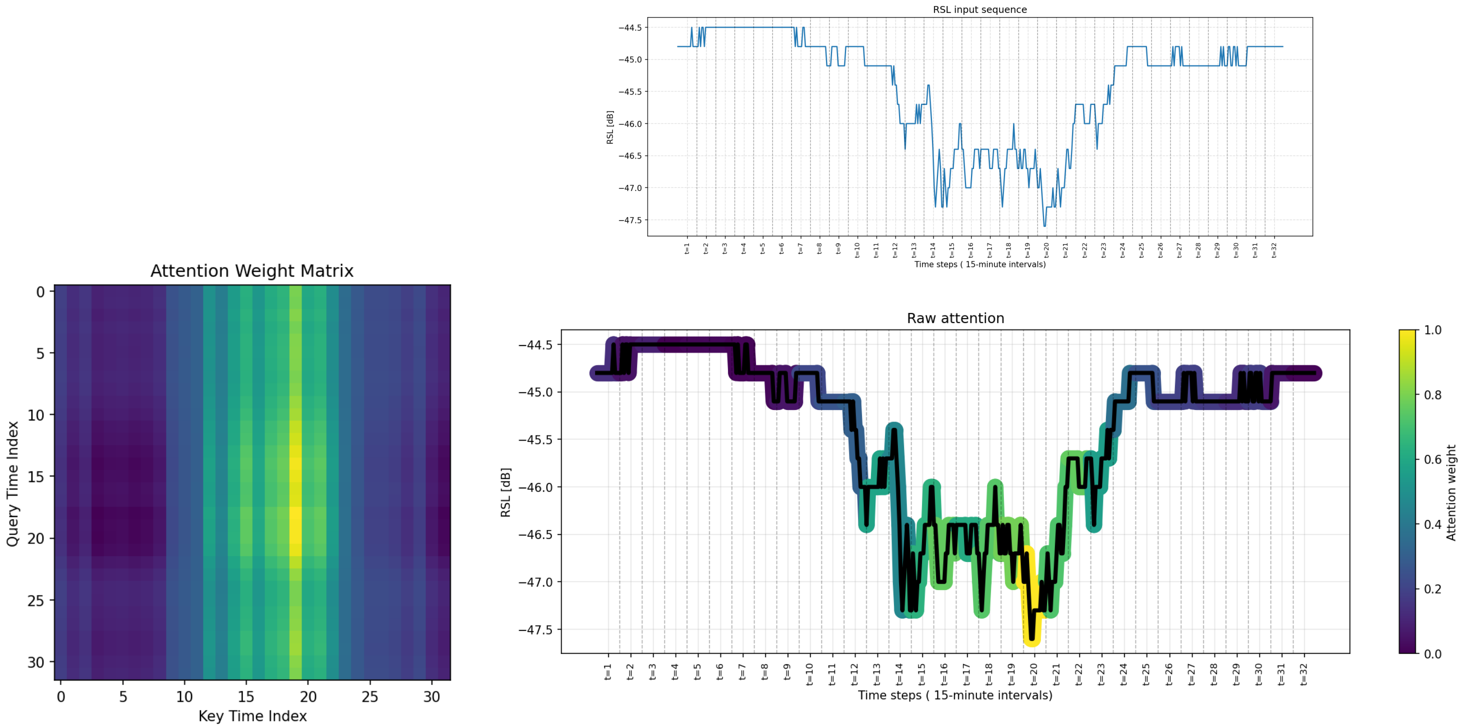
Case 1：single short rain event



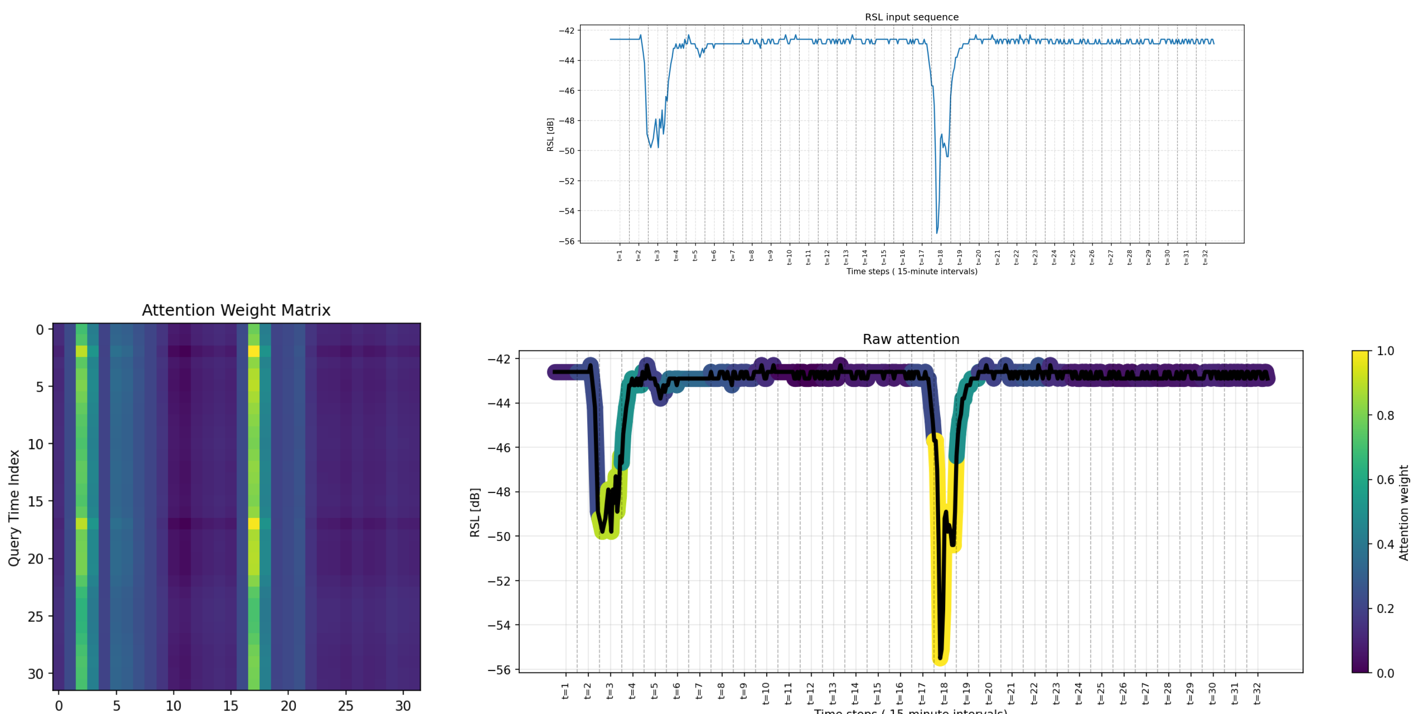




Case 2: single long rain event



Case 3: Two short rain events



While more advanced interpretability analysis methods exist, as discussed in [R1a], raw attention visualization already provides meaningful insight into the temporal focus and decision behavior of the proposed model.

We note that employing finer temporal tokens than the current 15-minute windows could potentially provide higher-resolution attention patterns and more detailed visualizations; however, such extensions, along with other interpretability approaches, are left for future work.

We therefore believe that the Transformer does not operate as a complete black box, but rather learns interpretable temporal attention patterns that correspond to physically meaningful rainfall dynamics.

<u>Reference:</u>

[R1a] Chefer, Hila, Shir Gur, and Lior Wolf. "Transformer interpretability beyond attention visualization." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021.