# From Neural Network to Temporal Logic: A Global Explainability Method for Time Series

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## Context:

Massive collections of time-varying data (i.e., time series, or data series in general) are becoming a reality in virtually every scientific and social domain. Examples of fields that involve data series include finance, environmental sciences, astrophysics, neuroscience, engineering, and multimedia. What is challenging in these data is that they are mainly highly multivariate, and also, the different dimensions that compose these data may originate from different sources.

Among time series-related analytical tasks, time series classification is a crucial and challenging problem in data science. To solve this task, various time series classification algorithms have been proposed in the past few years [1] and applied to many use cases. Standard data series classification methods are based on distances to the instances' nearest neighbors, with k-NN classification (using the Euclidean or Dynamic Time Warping (DTW) distances) being a popular baseline method [2]. Nevertheless, recent works have shown that ensemble methods using more advanced classifiers achieve better performance [3]. Following recent breakthroughs in the computer vision community, new studies successfully propose deep learning methods for time series classification [4], such as Convolutional Neural Network (CNN), Residual Neural Network (ResNet) [4], and InceptionTime [5].

However, recent deep learning approaches proposed in the literature lack interpretability and readability for the user. Explainability methods have been proposed in the literature, but those methods are mainly instance-based [4,6,7] (i.e., local explanation). Therefore, there is a need to move toward dataset-based explanation methods (i.e., global explanation). The latter means that the model, by its design or associated post-processing methods, has to provide explanations related to the general aspect of "belonging to a class".

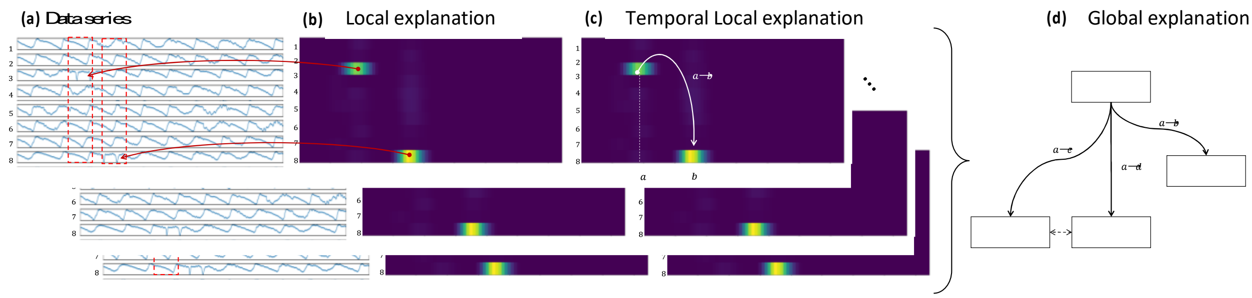


**Figure 1:** Explanation for time series

## Research Problem:

The latter can take different forms. The explanation can be subsequence-based, dimension-based (i.e., identify which dimension is important using methods like SHAP [8] or LIME [9]), or logic-based (i.e., express the explanation in formal logic predicates as Signal Temporal Logics (STL) [10]). However, there exist no methods that group all three criteria (i.e., sub-sequence and dimension-based expressed in temporal logics predicate) as well as benefit the classification power of recent convolutional neural network architectures.

Therefore, based on recent studies, the objective of this internship is to propose a new methodology that converts the CNN predictions into a temporal-based decision tree. The latter could propose optimal readability for the user and offer the possibility to logically express the explanation as the scale of the dataset (i.e., global explanation).

## Tasks:

During this internship, the student will do the following tasks:

- Acquire an exhaustive understanding of the literature on local and global explanations for time series classification and temporal logic.
- Propose and implement temporal-based decision trees that can embed the predictions of CNN methods.
- Evaluate the proposed solution on publicly available benchmarks (UCR-Archive [7]).
- Compare the proposed solution to the existing state-of-the-art methods.

## Required skills:

- M2 in Data science, Computer Science
- Strong analytical and programming (Python) skills

## Team and Location

This 5 months internship will take place within the computer science department at Ecole Normale Supérieure (45 rue d'Ulm, Paris 5), a member of PSL University, in the Valda team (led by Prof. Pierre Senellart) and supervised by Paul Boniol and Michaël Thomazo (Inria researchers at VALDA). We are interested in candidates considering the possibility of doing a PhD in the team after the internship.

If interested, please send your application to boniol.paul@gmail.com

## References:


1. Anthony Bagnall, Jason Lines, Aaron Bostrom, James Large, and Eamonn Keogh. 2016. **The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances**. Data Min. Knowl. Discov. 31 (2016).
2. Hoang Anh Dau and Anthony J. Bagnall and Kaveh Kamgar and Chin-Chia Michael Yeh and Yan Zhu and Shaghayegh Gharghabi and Chotirat Ratanamahatana and Eamonn J. Keogh: **The UCR time series archive**. IEEE/CAA Journal of Automatica Sinica. 2019
3. Anthony Bagnall, Jason Lines, Jon Hills, and Aaron Bostrom. 2015. **Time-Series Classification with COTE: The Collective of Transformation-Based Ensembles**. IEEE TKDE 27 (2015).
4. Hassan Ismail Fawaz, Germain Forestier, Jonathan Weber, Lhassane Idoumghar, and Pierre-Alain Muller. 2019. **Deep Learning for Time Series Classification: A Review**. Data Min. Knowl. Discov. 33, 4 (2019).
5. Hassan Ismail Fawaz, Benjamin Lucas, Germain Forestier, Charlotte Pelletier, Daniel F. Schmidt, Jonathan Weber, Geoffrey I. Webb, Lhassane Idoumghar, Pierre Alain Muller, and Francois Petitjean. 2020. **InceptionTime: Finding AlexNet for time series classiffication**. Data Mining and Knowledge Discovery 34 (7 Sept. 2020)
6. B. Zhou, A. Khosla, Lapedriza. A., A. Oliva, and A. Torralba. 2016. **Learning Deep Features for Discriminative Localization**. CVPR (2016).
7. Paul Boniol, Mohammed Meftah, Emmanuel Remy, and Themis Palpanas. 2022. **DCAM: Dimension-wise Class Activation Map for Explaining Multivariate Data Series Classification**. In Proceedings of the 2022 International Conference on Management of Data (SIGMOD '22). Association for Computing Machinery, New York, NY, USA, 1175–1189.
8. Scott M. Lundberg and Su-In Lee. 2017. **A unified approach to interpreting model predictions**. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 4768–4777.
9. Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. **"Why Should I Trust You?": Explaining the Predictions of Any Classifier**. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16). Association for Computing Machinery, New York, NY, USA, 1135–1144.
10. R. Yan, T. Ma, A. Fokoue, M. Chang and A. Julius, **Neuro-symbolic Models for Interpretable Time Series Classification using Temporal Logic Description**, in 2022 IEEE International Conference on Data Mining (ICDM), Orlando, FL, USA, 2022 pp. 618-627.