

Unlocking the potential of Time Series across different fields of application

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Introduction and Relevance

Introduction



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Time series analysis is a powerful tool used to extract insights from data collected over time, and its applications span across a wide range of fields of application.

By analysing trends, patterns, and seasonal variations, time series models allow for **accurate forecasting** and **anomaly detection**.

Beyond forecasting, classifying time series data allows us to group **similar patterns and behaviors**, adding even more depth to its utility.

Moreover, the methodologies applied in one area can often be adapted to others, allowing **knowledge sharing and innovation** across different domains.

Aim of this work

How the same methodologies used to analyse temporal data can be applied across seemingly unrelated fields.



Research Methodology



Application: AGN

Dataset and features

For further details on the dataset: **De Cicco+2021**

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-1

Activation map: All features





All Features



For each neuron, we calculated the global mean and standard deviation. Features are in red if:

mean < global_mean - 2*global_std

or

mean > global_mean + 2*global_std

Application: Financial Data

Dataset and features

Statistical Features

Amplitude	Freq2_harmonics_amplitude_
AndersonDarling	Freq2_harmonics_amplitude_
Autocor_length	Freq2_harmonics_amplitude_
Con	Freq2_harmonics_amplitude_
Eta_e	Freq2_harmonics_rel_phase_
FluxPercentileRatioMid20	Freq2_harmonics_rel_phase_
FluxPercentileRatioMid35	Freq2_harmonics_rel_phase_3
FluxPercentileRatioMid50	Freq3_harmonics_amplitude_
FluxPercentileRatioMid65	Freq3_harmonics_amplitude_
FluxPercentileRatioMid80	Freq3_harmonics_amplitude_
Freq1_harmonics_amplitude_0	Freq3_harmonics_amplitude_
Freq1_harmonics_amplitude_1	Freq3_harmonics_rel_phase_:
Freq1_harmonics_amplitude_2	Freq3_harmonics_rel_phase_2
Freq1_harmonics_amplitude_3	Freq3_harmonics_rel_phase_
Freq1_harmonics_rel_phase_1	Gskew
Freq1_harmonics_rel_phase_2	LinearTrend
Freq1_harmonics_rel_phase_3	MaxSlope





SOM - 1

- Statistical Features
- Preliminary step: Isolation Forest with 5% of contamination. 4989 outliers found.
- Neighborhood function: Gaussian.
- The pies on the activation map show the distribution of outliers/not-outliers in output from the Isolation Forest.





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Feature Index

- 0: Amplitude
 1: AndersonDarling
- 2: Autocor_length
- 4: Eta_e
- 5: FluxPercentileRatioMid20
- 6: FluxPercentileRatioMid35
- 7: FluxPercentileRatioMid50
- 8: FluxPercentileRatioMid65
- 9: FluxPercentileRatioMid80
- 10: Freq1_harmonics_amplitude_0
 11: Freq1 harmonics amplitude 1
- 12: Freq1 harmonics amplitude 2
- 13: Freq1 harmonics amplitude 3
- 14: Freq1 harmonics rel phase 1
- 15: Freq1 harmonics rel phase 2
- 16: Freq1_harmonics_rel_phase_3
- 17: Freq2_harmonics_amplitude_0
- 18: Freq2_harmonics_amplitude_1
- 19: Freq2_harmonics_amplitude_2
 20: Freq2_harmonics_amplitude_3
- 20. Heq2_harmonics_amplitude_3
 21: Freq2_harmonics_rel_phase_1
- 21: Freq2_harmonics_rel_phase_1
 22: Freq2_harmonics_rel_phase_2
- 23: Freq2_harmonics_rel_phase_3
- 24: Freq3 harmonics amplitude 0
- 25: Freq3_harmonics_amplitude_1
- 26: Freq3_harmonics_amplitude_2
- 27: Freq3_harmonics_amplitude_3
- 28: Freq3_harmonics_rel_phase_1
- 29: Freq3_harmonics_rel_phase_2
- 30: Freq3_harmonics_rel_phase_3
- 31: Gskew
- 32: LinearTrend
- 33: MaxSlope
- 34: Mean
- 35: Meanvariance
- 36: MedianAbsDev
- 37: MedianBRP
- 38: PairSlopeTrend
 39: PercentAmplitude
- S9: PercentAmplitude
- 40: PercentDifferenceFluxPercentile
- 41: PeriodLS42: Period fit
- 42: Period_
 43: Psi CS
- 43: PSI_C3
 44: Psi_eta
- 44: PSI_eta
 45: 031
- 46: Rcs
- 47: Skew
- 48: SmallKurtosis
- 49: Std



For each neuron, we calculated the global mean and standard deviation. Features are in red if:

mean < global_mean - 2*global_std

or

 $mean > global_mean + 2*global_std$

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SOM - 2

- Statistical Features
- Preliminary step: Isolation
 Forest with 5% of contamination. 4989 outliers found.
- Neighborhood function: Mexican Hat.
- The pies on the activation map show the distribution of outliers/not-outliers in output from the Isolation Forest.



Neuron (1, 8)



25 -









Neuron (4, 4)

Neuron (5, 7)

Neuron (7, 3)

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• 49: Std

Non-outliers

Outliers

35000

30000

- 25000

20000

15000

10000

- 5000



Conclusions



Cross-Disciplinary Insights

• Time series can be adapted across various domains, demonstrating that innovations in one field can drive advancements in others.



Identification of Similar Objects

• This method allows for the identification of objects with similar characteristics, such as classifying Active Galactic Nuclei based on specific features.



Anomaly Detection and Outlier Identification

• Time series analysis is crucial for detecting anomalies, particularly useful in fields like banking for identifying outliers that may indicate fraud or other irregular activities.

Thank you!



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All features vs No-colors

Activation map: All features vs No-colors



Mapping QSO: All features vs No-colors



Activation map and AGN Types: All features vs No-colors







No-colors



For each neuron, we calculated the global mean and standard deviation. Features are in red if:

or

mean < global_mean - 2*global_std

mean > global_mean + 2*global_std

Examples of time series in specific neurons

Cella (4,2)















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Neuron (8, 8)

No IF outliers





Cella (0,8)







