



ONLINE HACKATHON

Quantum code challenge

Innovative Quantum Algorithms
for Smart Cities

22-25 OCTOBER 2024

THE EVENT IS ENDORSED BY



PSC MIMIT - FSC 2014-2020 Programma di supporto tecnologie emergenti nell'ambito del 5G Asse I Progetto "CDL - Casa delle Tecnologie Emergenti di Cagliari" CUP G27F22000040008



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UNIVERSITÀ DEGLI STUDI
DI CAGLIARI



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THE TASK

The Problem

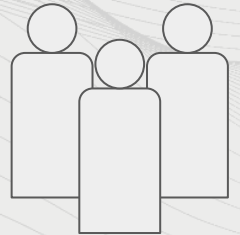
Our Solution

Some Results



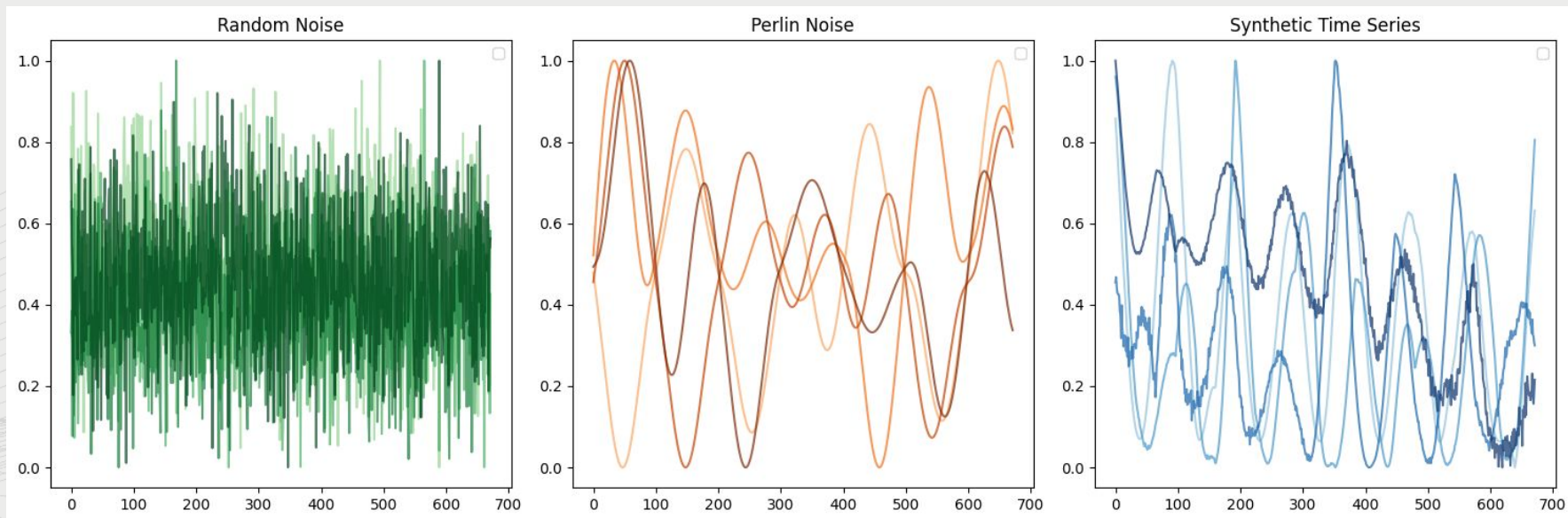
PROBLEM STATEMENT

- We were assigned a task which involved **four different datasets**: *particulate matter*, *pollution*, *weather* and *unique attendance*. The goal was to create a model that could find and notify anomalies.
- We focused on **unique attendance**. We wanted to understand the variation in the number of people in different areas of the city and how we could identify anomalies.
- As anomalies, we hypothesized to report possible variations in gatherings of people in cases of **over tourism** or **pandemic crisis** or other purposes.



SYNTHETIC DATA GENERATION

- To evaluate our solution, we generated three different type of **synthetic data**.
- We expect a good model to recognize all the artificial data as ***anomalous***.



PROPOSED SOLUTION: Quantum Temporal Kernels

- Starting from the theoretical background from [1], we implemented a **Quantum Kernel with temporal dependency** able to compute similarity between time series.
- In particular, we used

$$C(x_t) = \text{Emb}(x_t) \cdot U(t)$$

where $\text{Emb}(x_t)$ is a **static mapping** and U introduces the **temporal dependency**.

- Finally, the kernel computes the **similarity** between two series $x^{(t)}$ and $y^{(t)}$ is given by

$$K(x^{(t)}, y^{(t)}) = \sum_{t \in T} \langle C(x_t) | C(y_t) \rangle$$

RESULTS

- We compared our results on a test set (*non-anomalous* data) and the synthetic ones.
- We compared our approach with four different classical kernel methods.
- Standard classical kernels:
 - Ill-suited for time series, but very fast
- Dynamic Time Warping:
 - Specialized for time series, but required hours
- Our method:
 - Tailored for time series, and quite fast

For further details see our [GitHub repo](#). 🐶



Training and testing datasets of 50 samples

	Accuracy			
	Non-Anomalous	Noise	Perlin	Synthetic
Linear	82	2	6	60
Poly	66	72	100	96
RBF	78	4	10	66

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Merlin	80	76	80	92

**Thanks for your
attention!**

