G-CMP: Graph-enhanced Contextual Matrix Profile for unsupervised anomaly detection in sensor-based remote health monitoring

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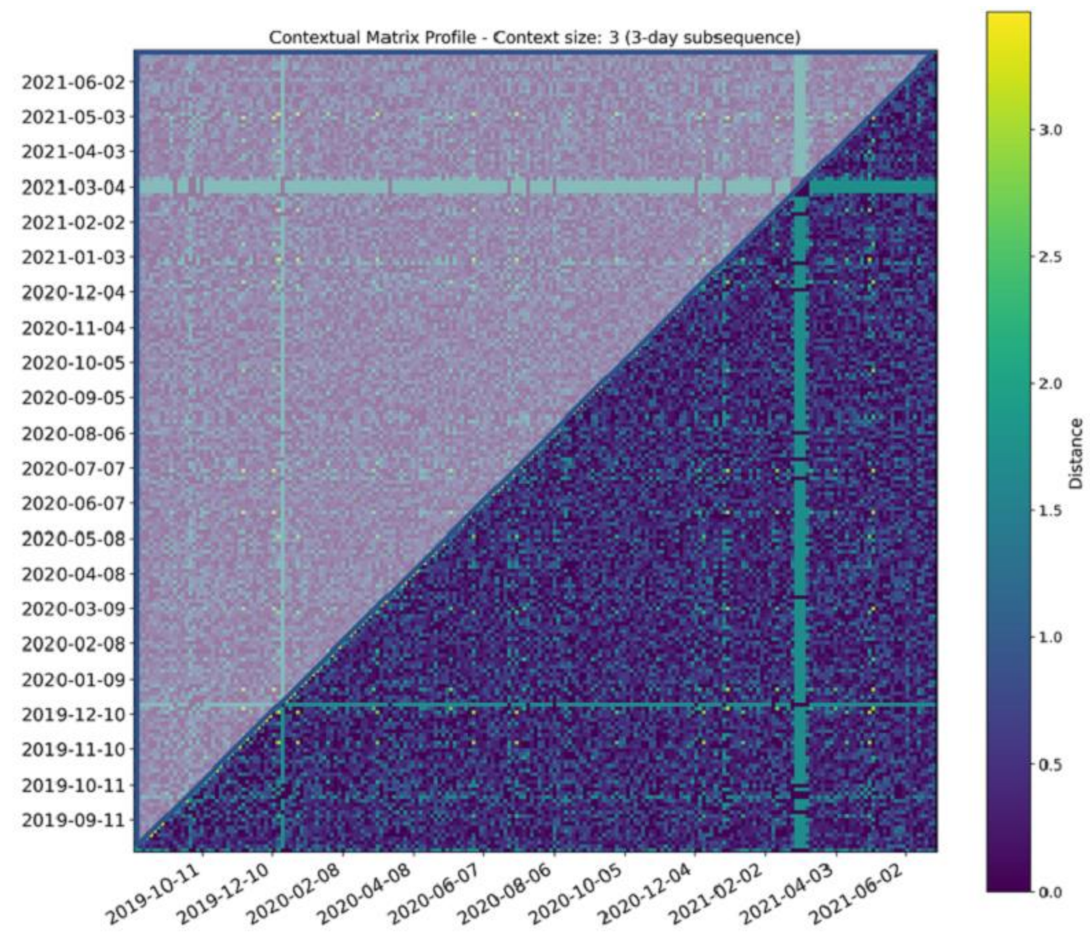
INTRODUCTION

Our paper addresses the problem of temporal anomaly detection (AD) in real-world sensor based remote health monitoring

Real-world sensor-based remote health monitoring challenges	
Noisy data/labels	Need for low alert rate
Data drift	Point anomalies
Streaming data	Contextual anomalies
Multidimensional data	Collective anomalies
Scoring anomalies	Minimal tuning
Unsupervised detection	Interpretability
Need for high recall	Scalability

- Current unsupervised methods use autoencoders, contrastive learning, or attention based GCNs which suffer from complexity, assumption of "normal" training data, low scalability and interpretability, and need for data refresh
- We use *self-supervised graph representation learning on top of the Contextual Matrix Profile (CMP)* and show its effectiveness in detecting adverse events in a remote health monitoring of people living with dementia
- This method is generalisable and can be adapted for AD in temporal vision tasks

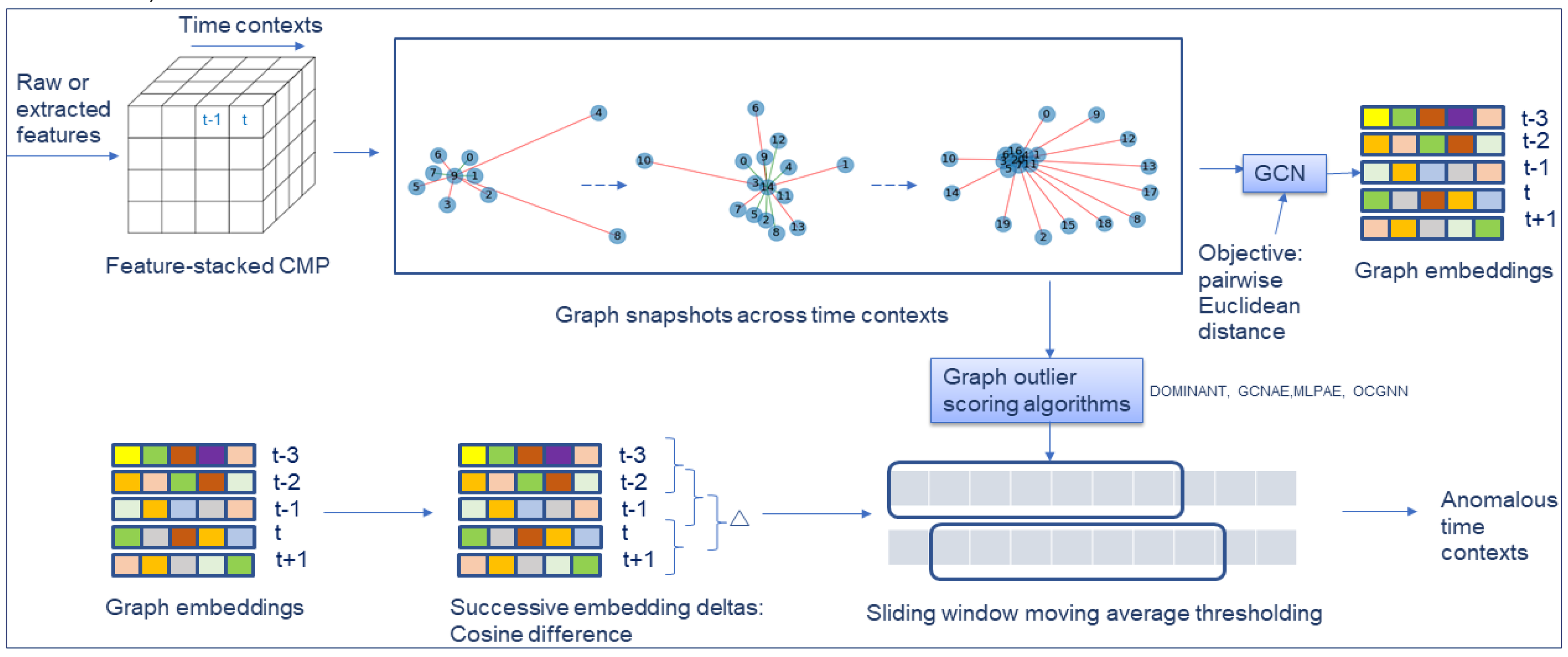
CONTEXTUAL MATRIX PROFILE



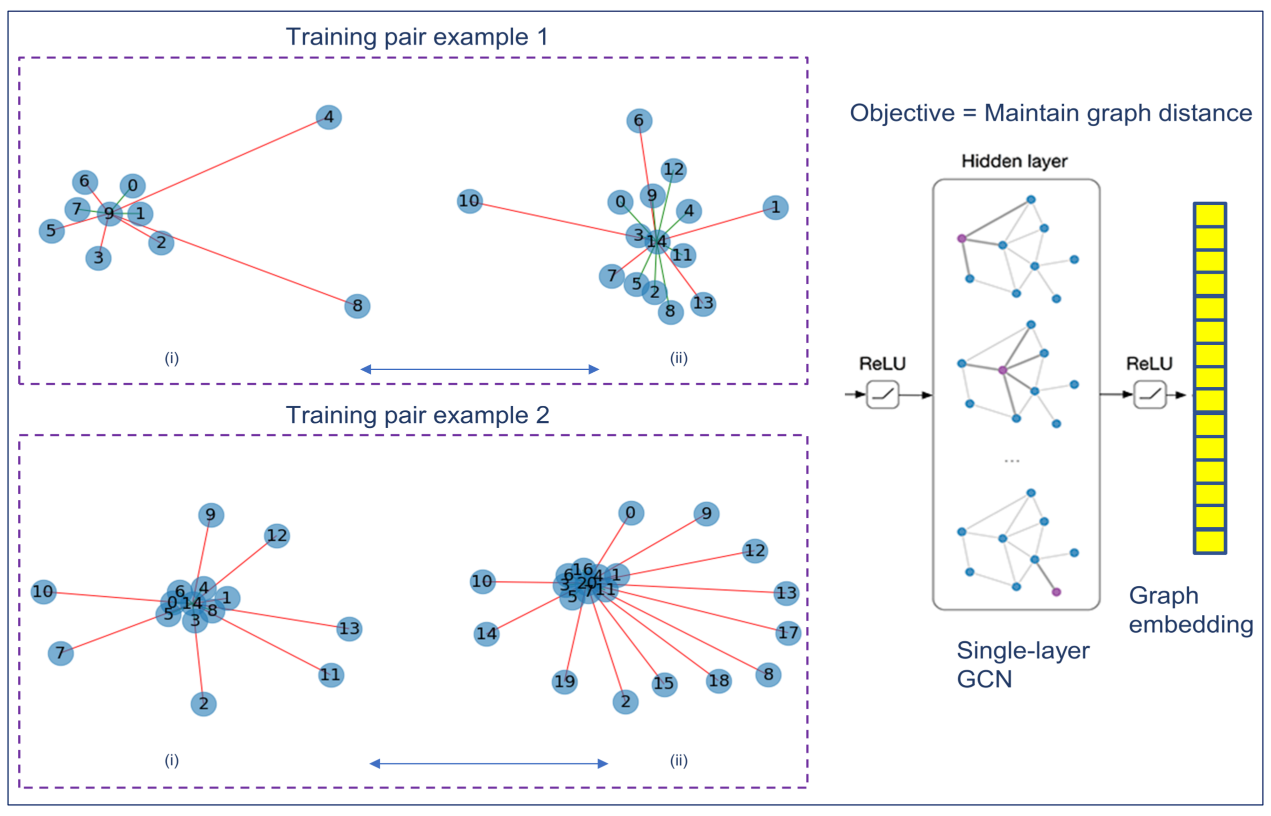
- The CMP [1] is a pairwise nearest neighbour distance matrix between user-defined time blocks or "contexts" containing time series subsequences
- Computation of the CMP is ultra-fast, as it is based on the Matrix Profile (MP) which uses the Fast Fourier Transform for the z-normalised distance computation [2]
- The green bands in the CMP heatmap above, indicate anomalies
- The CMP provides the foundation for an exact, domain-neutral, denoised, intuitive and interpretable AD methodology [3]

METHODOLOGY

Multimodal sensor data is used to derive raw or extracted features, and feature-wise CMPs are created. Feature-stacked CMP distance matrices are converted to evolving time context graphs – the central node of each star graph is a time context and the outer nodes represent previous time contexts. Outer node features are the feature-wise distances to the central node. We apply graph learning to obtain embeddings, and use these to evaluate anomalousness of a time context. We use a single-layer self-supervised GCN and also evaluate existing graph outlier scoring algorithms on top of context graphs: MLP AE, DOMINANT, One-class GNN, and GCN AE.

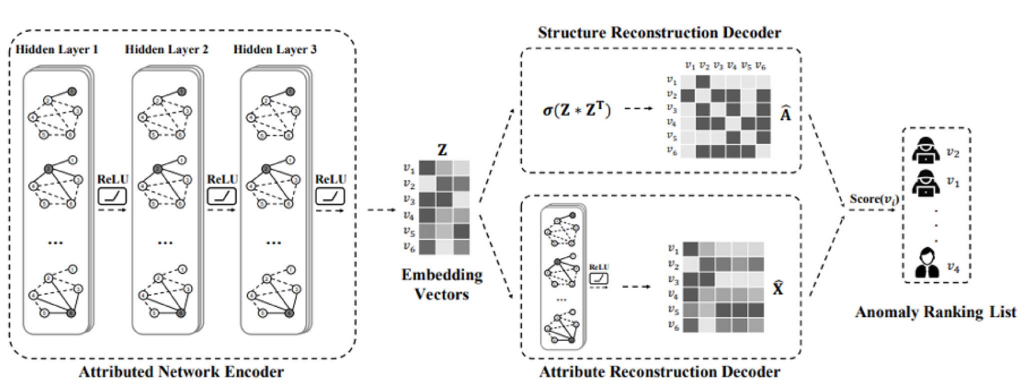


Graph representation learning pipeline

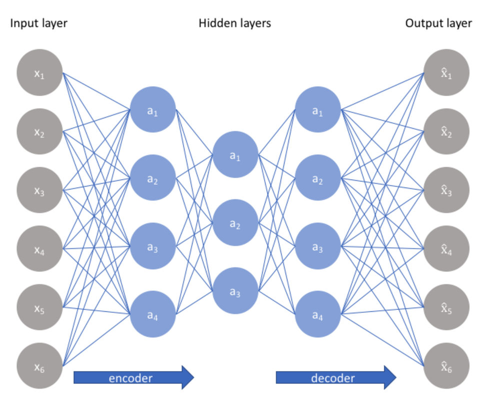


Self-supervised GCN Training

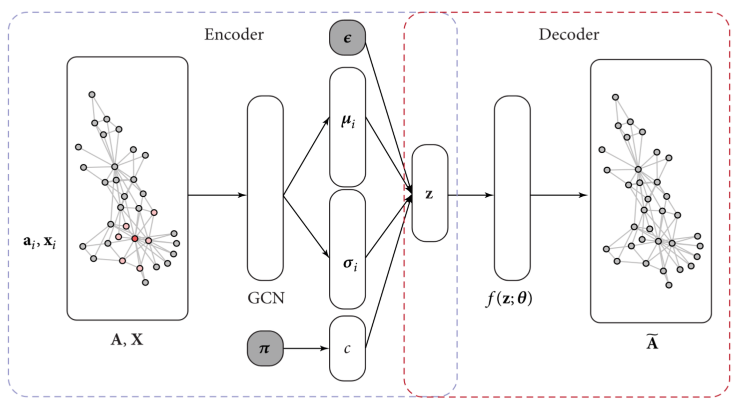
GRAPH OUTLIER ALGORITHMS



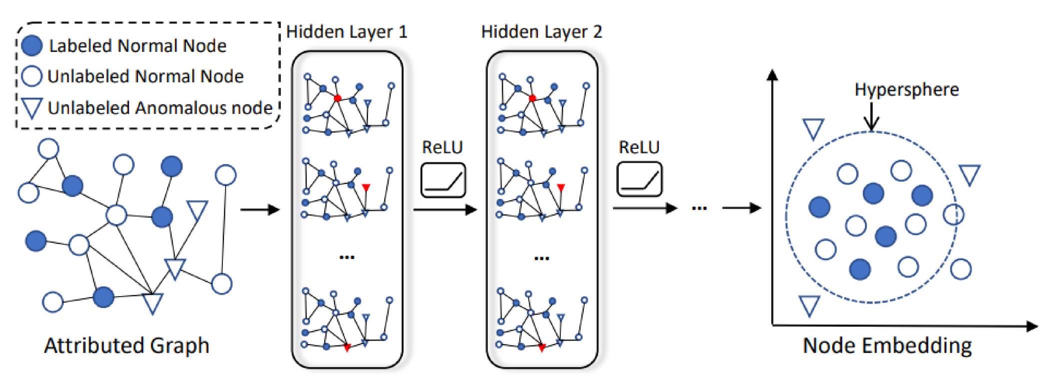
DOMINANT [4]



MLP AE [5]



GCN AE [6]



OCGNN [7]

EXPERIMENTS AND RESULTS

- Experiments were conducted on remote health monitoring datasets collected from the homes of 65 people living with dementia from the Minder research study [8] for Agitation and Fall events over a total of 18,710 days with 183 labelled adverse events (anomalies)
- Hyperparameters - graph pairs, number of layers, dropout rate, training epochs, embedding dimension - were tuned on a separate dataset of 15 patients with urinary tract infection (UTI)
- Benchmark methods included Angle-based outlier detection, Copula-based outlier detection, Lightweight online detector of anomalies and multidimensional CMP (see [3])
- Evaluated using Recall, Alerts raised, Patients with > x% recall (to determine generalisability)

Model	Recall%	Alert rate%	Patient validity
DOMINANT	73.62	5.91	36/42
GNN	**73.97**	**5.66**	**37/42**
GCN AE	67.38	5.41	31/42
MLP AE	60.57	5.52	28/42
Benchmark (see [3])	71.96	5.82	36/42

Agitation cohort results

Model	Recall%	Alert rate%	Patient validity
DOMINANT	57.97	5.53	16/23
GCN AE	63.77	5.60	17/23
MLP AE	52.90	5.47	16/23
GNN	**72.46**	**5.85**	**19/23**
Benchmark (see [3])	71.74	6.45	19/23

Falls cohort results

CONCLUSIONS

- ✓ Representation learning on top of graph-enhanced CMP outperformed multidimensional CMP and SOTA methods for anomaly detection
- ✓ Creating time context graphs makes for a feature-agnostic, scalable approach. Graph structure does not change as new features are added
- ✓ Cross-feature correlations are addressed
- ✓ The modular pipeline allows for flexibility in graph construction and self-supervision mechanisms
- ✓ Computer vision applications include using CMPs to represent temporal sequences of visual features with GNNs detecting visual anomalies in the feature stream, and classification of objects across temporal sequences

FUTURE WORK

- Use of sparse graphs to amplify anomalousness
- Contrastive learning for self-supervision
- Addressing "cold-start" problem by pre-training self-supervised GCN using similar time context graphs from different subjects and domains
- End-to-end learning – feature extraction to representation learning

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