Computer Vision for Anti-Money Laundering in Time-Varying Transaction Networks

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Network analytics has become an indispensable tool for anti-money laundering (AML), given the complexity of criminal schemes involving numerous transactions and parties to conceal illicit funds. Over the years, the focus has shifted from analyzing individual network positions via centrality measures to capturing complex interactions using graph neural networks (GNNs) and flow detection methods (Deprez et al., 2025b).

A segment of the literature focuses on identifying specific network motifs associated with money laundering. Although GNNs can be extended to capture complex motifs and topologies (Egressy et al., 2024), many existing approaches are tailored to very specific patterns (Lee et al., 2020; Li et al., 2020; Deprez et al., 2025a). Furthermore, these methods often utilize minimal information, incorporating at most the transaction amount and direction.

In this work, we propose a novel method to represent sub-graphs as visual images to capture intricate patterns within the transaction network. We build upon the work of Deprez et al. (2025a), who demonstrated that effective, scalable AML can be achieved using information restricted to the second-order neighbourhood of a node. We combine various summary statistics by carefully defining distinct channels in our visual representation, moving beyond the standard RGB format. Specifically, we map the node's local topology onto a fixed-size grid, where surrounding pixels encode the aggregated statistics of neighbours. By utilizing high-dimensional tensors, we explicitly link these statistics; for example, the minimal and maximal values of a specific neighbourhood sub-region share the same pixel coordinates but occupy different channels. This contrasts with classic tabular data, where such spatial relationships are lost among feature columns.

We address the dynamic nature of money laundering by generating temporal snapshots of the transaction network, resulting in a video-like sequence of trans-

action behaviour for each node. We introduce *transaction echoes*, where transactions are not seen as binary connections (merely present or absent). Instead, past transactions remain present but their signal strength decays exponentially over time. This decay mechanism acts as a continuous memory state, overcoming the limitations of rigid time-windowing approaches which often sever the link between related transactions occurring across window boundaries. This enables the analysis of network structures and transaction flows that span multiple time steps.

Our experiments combine different approaches to analyse these feature videos and compare them against several baseline methods. The results demonstrate that our novel approach yields high detection rates comparable to complex GNN architectures, but with significantly lower computational overhead. This suggests that summarising network structures based on simplified visual statistics offers a robust and efficient alternative for real-world AML systems.

References

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