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Using Graph Representation Learning to Passively Learn Imaging Protocols

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Introduction

Imaging protocol management is a complex, unsolved problem. Systems like HL7 or DICOM only record the "general procedure type" (e.g., "MR BRAIN W/WO") but not the specific protocol performed (e.g., Stroke, TBI, Pediatric Tumor), hindering data-driven monitoring and optimization. Worse: protocols, the exams' "recipe", can in reality be explicit (e.g. in a book) or implicit (remembered or modified by a technologist); and the information location is ill-defined. We propose to use machine learning to passively learn imaging protocols from the technical parameters in DICOM metadata, leading to a more accurate description and new protocol management capabilities.

Hypothesis

We previously built a software platform that analyzes DICOM metadata on-the-fly to construct a new, highly granular ontology of imaging operations. Key features include the extraction of new concepts beyond DICOM including the concepts of examinations, acquisitions and volumes, and access to all technical parameters (e.g., TE, TR, resolution, etc) of each volume. Our hypothesis is that we can use this data platform to automatically learn imaging protocols with machine learning by analyzing the technical parameters of acquisitions.

Methods

Passively learning imaging protocol amounts to automatically grouping together exams with similar acquisitions. This is a difficult unsupervised clustering problem as different exams have different numbers of acquisitions - requiring computing distances between spaces of different dimensions. We propose, for the first time, to represent exams as graphs in which each node is an acquisition with its technical parameters as node attributes. We then use graph neural networks to automatically learn an embedding for each exam that can be used for many downstream machine learning applications.

Results

After training our graph neural network and using uniform manifold approximation and projection (UMAP) to visualize our embeddings, we found that our embedding could successfully, geographically regroup similar exams (Figure 1). Importantly, our model produced similar embeddings in presence of repeated acquisitions within examinations, but different embeddings when acquisitions were missing (Fig 2). Figure 3 shows that community analysis in regions of the manifold can further divide the data into distinct subprotocol communities, solely based on technical parameters.

Conclusion

We show that transforming imaging exam metadata into graphs and subsequently training a graph neural network, allows us to passively learn imaging protocols simply from the technical parameters of the acquisitions.

Statement of Impact

Passive protocol learning will radically transform imaging operation management allowing new deviation detection capabilities, protocol normalization across scanners, and the assessment of protocol-specific statistics crucial for optimizing patient scheduling.

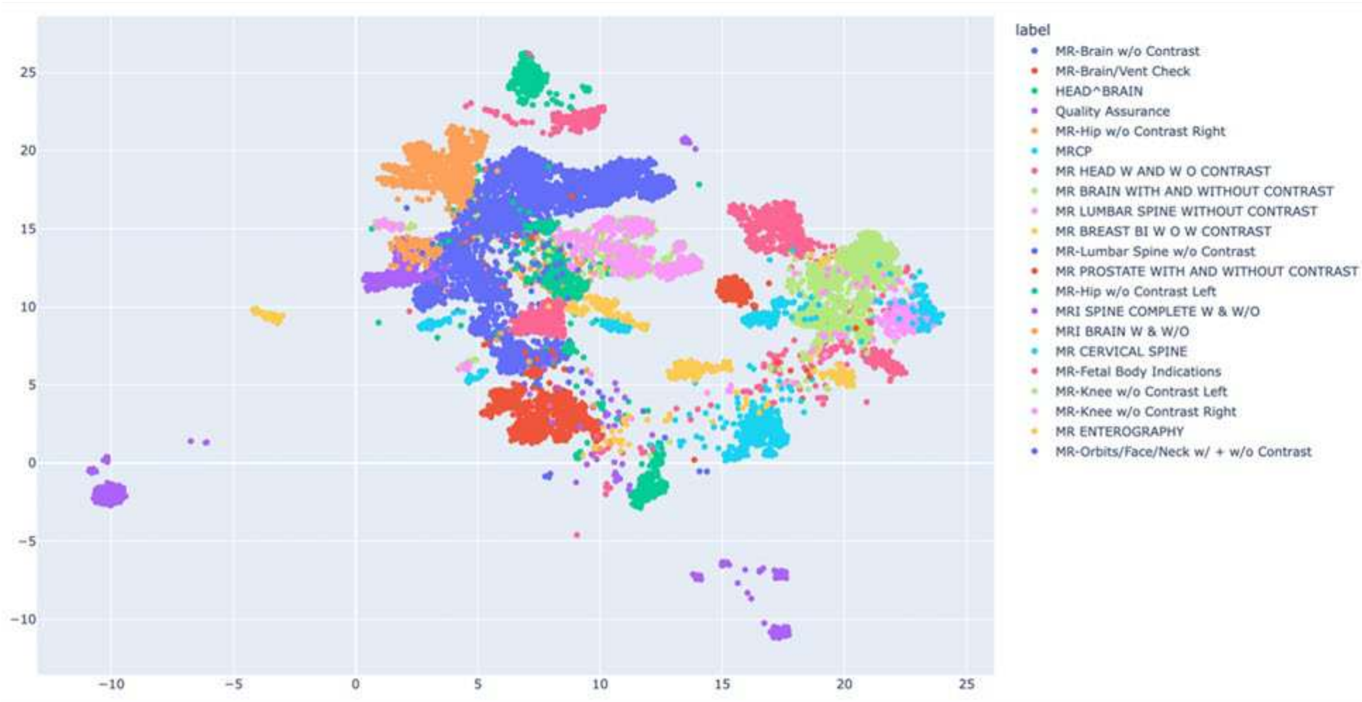

Figure 1: UMAP dimension reduction of GNN exam embedding. Here we show that different anatomical areas identified by their “Study Description” are in distinct locations, and that exams of the same study description are spread out in specific patterns representing distinct sub-protocols. Importantly we show that lateral protocol (left vs right) occupies the same space and that unique exams (like Quality Assurance) as in distinct areas. This shows our GNN is able to translate imaging exam metadata into distinct embeddings that hold semantic information unique to each protocol.

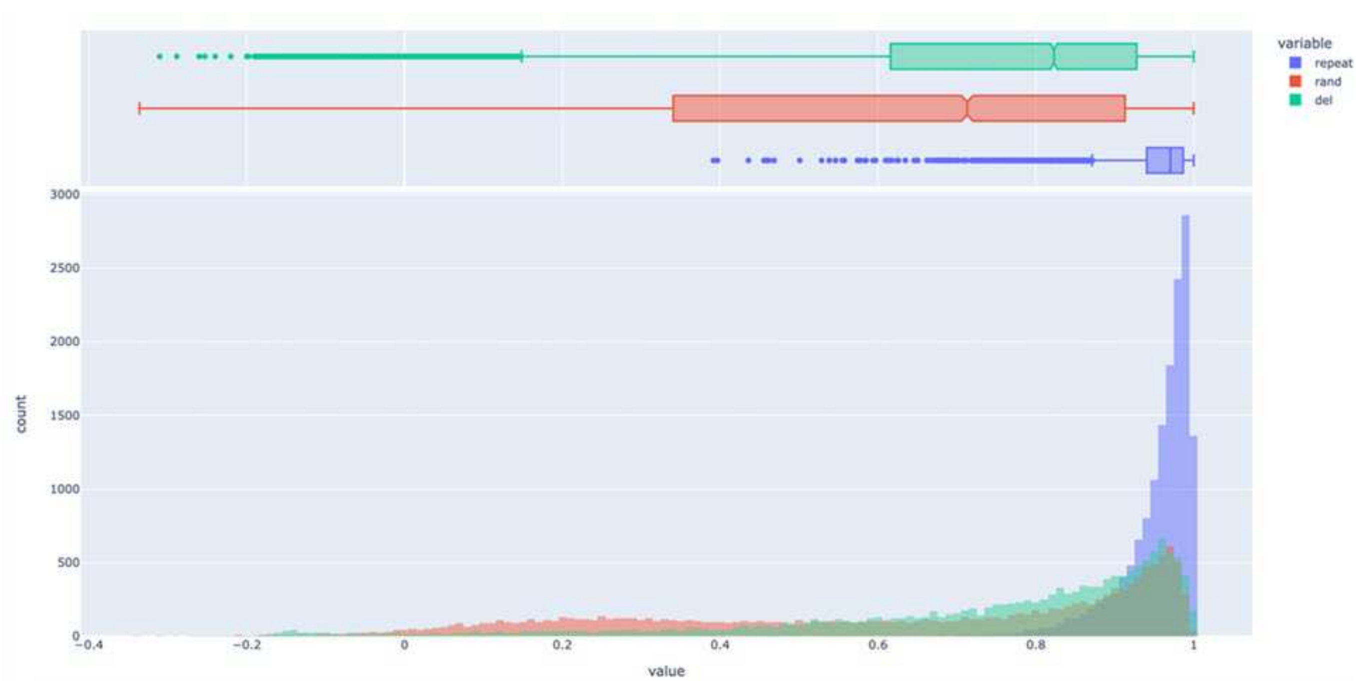

Figure 2: In order to determine if similar embeddings are produced, we computed the correlation between different pairs of embeddings: 1) normal embeddings (unaltered graph) and artificial repeat; 2) normal embeddings and deleted acquisition; 3) normal embeddings and augmented graph (where the added node have random attributes). The distributions of correlation values show a high level of similarity in presence of repeated acquisitions, indicating robustness of our embedding to repeats. As expected, the correlations are much lower with other perturbations which is promising to identify protocol deviations.

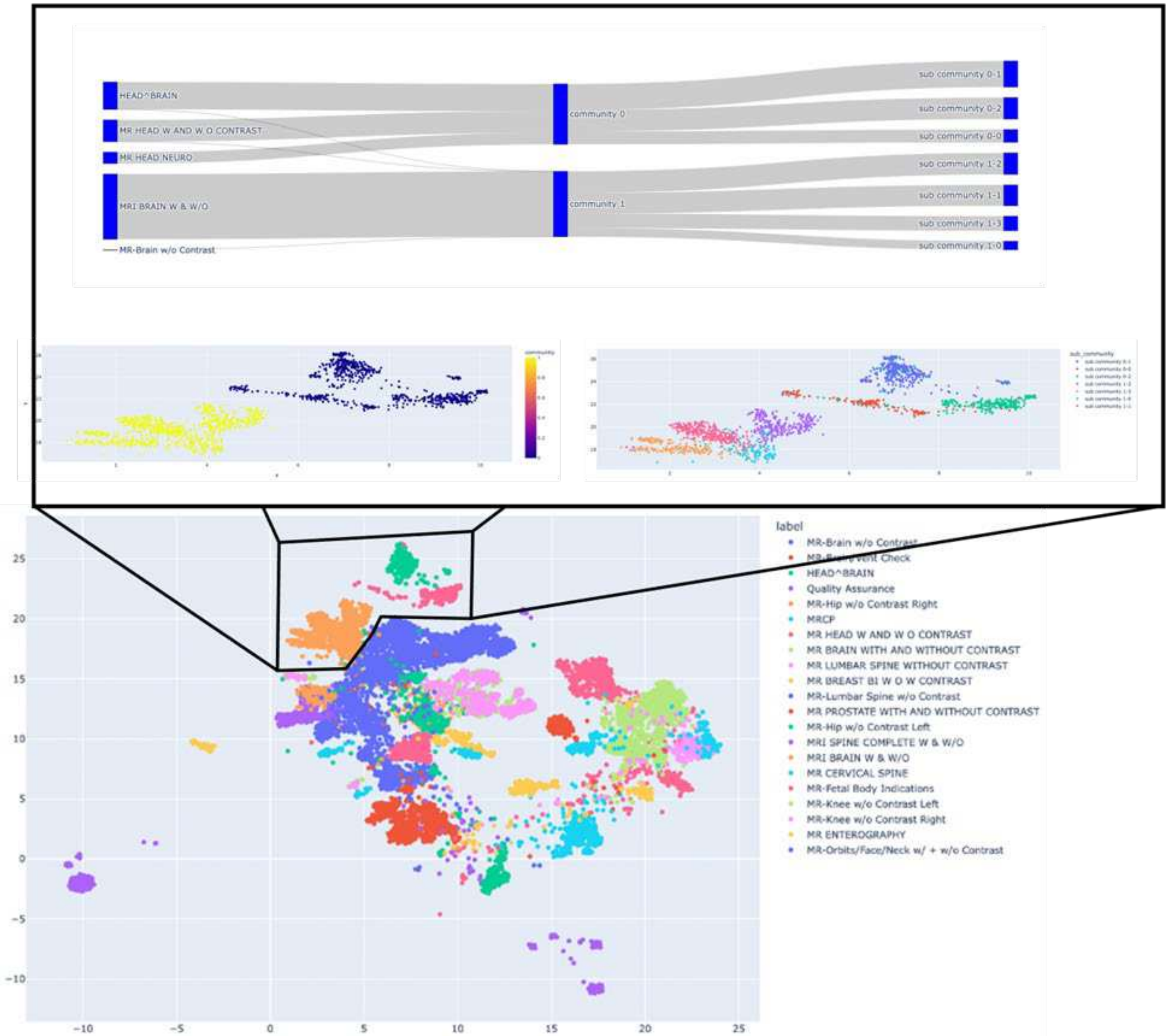

Figure 3: Community analysis (top part) of all exams found in the highlighted region (bottom part). The community analysis was based on a combination of the Louvain Community Detection Algorithm and a modified version of the Jonker-Volgenant algorithm. The results indicate that our model has the ability to isolate clusters and sub-clusters that represent distinct imaging protocols based solely on technical parameters, effectively demonstrating protocol learning

Keywords
Imaging Protocol learning; Graph Neural Network; Graph Representation Learning