Aniruddha Mukherjee Research Projects

(Working Paper) **EDIT-BERT: Emotion Detection and Integrated Transmission using Transformer Architecture for Semantic-Text and Graph Data**

Emotions on social media are expressed not only in text but also in the context of how that text is shared over a social graph. In this paper, we propose Emotion Detection and Integrated Transmission using BERT (EDIT-BERT) architecture, a novel transformer model that integrates the detection and transmission of emotions from both text and graph data. Our model incorporates an emotion detection layer that uses a feedback loop to combine the pre-classified word emotions with the predicted graph-transmission path, and a graph transformer layer with the following properties: (i) the attention mechanism is a function of the temporal emotion vectors, as well as the spatial weighted neighborhood influence for each node, (ii) the positional embedding is a Kernel distance weighted vector, (iii) a generalized attention mechanism that uses a vector-attention over a weighted matrix of neighborhood node embeddings, and (iv) incorporates a mechanism to model a graph transformer to contexts where the edge weights are unobserved through an affinity matrix and a unique weighted sampling scheme. We evaluate our model on a proprietary Twitter dataset related to COVID- 19 that we collected and contains 10 million unique tweets that have been re-twitted 40 million times. We show that the EDIT-BERT performs better prediction measures than a simi- lar model that does not incorporate neighborhood information and the feedback loop between the graph diffusion layer and emotion detection. We also share our dataset for public use. Our main contribution is to propose a novel transformer architecture that can integrate semantic-dependent and context- dependent emotion classification and transmission prediction in a unified framework. Our model generalizes to other do- mains where text and graph data are involved, such as news networks, social media analysis, and rumor detection.

(Submitted Paper to CVPR) **DL3DV-10K: A Large-Scale Scene Dataset for Deep Learning-based 3D Vision**

This paper signifies a substantial advancement in the field of deep learning-based 3D vision, with a particular emphasis on Neural Radiance Fields (NeRF). NeRF, a topic of considerable importance in current computer science and computer vision research, provides a novel methodology for synthesizing new views of complex 3D scenes from sparse 2D observations. The paper introduces DL3DV-10K, an exceptionally comprehensive dataset featuring 51.2 million frames from 10,510 videos captured across 65 types of point-of-interest locations. This dataset, which includes both bounded and unbounded scenes with varying levels of reflection, transparency, and lighting, serves as a pivotal resource for benchmarking and exploring deep learning-based 3D analysis. The paper provides an exhaustive benchmark of recent Novel View Synthesis (NVS) methods on DL3DV-10K, offering invaluable insights for future NVS research. Furthermore, an innovative pilot study demonstrates the potential of learning a generalizable NeRF from DL3DV-10K. This highlights the necessity of such a large-scale scene-level dataset for propelling advancements in 3D representation learning. The significance of this work is underscored by its potential to establish a foundation model for learning 3D representation, a critical advancement in the field of 3D vision.

(Work in Progress) **Bayesian Network Clustering for Latent Processes**

In this paper, we are developing a Bayesian regularized clustering model for network analysis of latent processes. The model is based on the Stochastic Block Model (SBM) with regularization for imposing sparsity constraints. The paper uses Random Graph Theory to propose graphical models that can accommodate single-edge as well as block-structure that may be present in large graphs. The benefits of joint graph and substructure recovery are that large-scale structure can help estimate graph edges better, and data-driven discovery of graph structure can help edge inclusion probability estimation better. To define blocks in multiple graphs, the authors introduce a novel Bayesian non-parametric prior, specifically, they propose a Dependent Dirichlet process-based prior for defining clusters. The domain of learning block structure in graphical models is categorized into two main strategies, namely, (i) regularization-based methods, and (ii) imposing structure on the precision matrix of a graph. In the regularization-based methods, a block structure is learned by first learning a sparse graphical structure by estimating a shrinkage estimator for the precision matrix as in G-LASSO, where every block is characterized by its own regularization parameter. In the second paradigm, it is common to consider a Gaussian Graphical Model (GGM) with a sparse Covariance matrix. This paper focuses on GGM models with sparse covariance matrix estimation. We test the model using data from the COVID-19 pandemic, where the infection propagation dynamics was latent and unobserved due to the asyptomatic nature of COVID-19. We demonstrate that the model has significant predictive power.