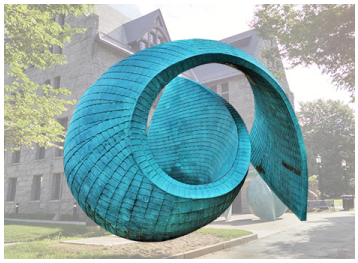

UNIVERSITY OF RHODE ISLAND

Department of Mathematics
and Applied Mathematical Sciences

Applied Mathematics and Scientific Computing Seminar

Location: Lippitt Hall 205

Time: Monday, October 2, 2023, 1:00pm

Low-rank data imputation using Hadamard deep autoencoders with applications to fragmented trajectory reconstruction of collective motion

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Abstract: Data imputation is an essential preprocessing step in statistical learning that is to be performed before any technical analysis is conducted on partially observed data. Data originating from natural phenomena is low-rank due to diverse natural dependencies that a low-rank technique should primarily emphasize during the imputation. Thus, we present an extended deep autoencoder for low-rank data imputation that we train only on the fully observed portion of the data by defining its loss function as the Hadamard product of a binary indicator matrix with the absolute difference between the outputs and the labels. This indicator matrix is of the same size as the data matrix, which has ones corresponding to the observed entries of the data matrix and zeros elsewhere. While low-rank data imputation is widely applicable across disciplines, here we focus on the reconstruction of fragmented trajectories of collective motion. Learning the dynamics of collectively moving agents such as fish or humans is an essential task in research. Due to natural phenomena such as occlusion or change of illumination, the multi-object methods tracking such dynamics may lose the tracks of the agents which may result in fragmentations of trajectories. Thus, we defragment the trajectories using our Hadamard deep autoencoder (HDA) in which the observed and unobserved segments of the trajectories are treated as observed and unobserved portions of data, respectively. The trajectory matrix of the agents practicing collective motion is low-rank due to mutual interactions and dependencies between the agents that we utilize as the underlying pattern that HDA codes during its training. The performance of this HDA is compared with that of a matrix completion scheme in the context of low-rank data imputation.