**An empirical Bayes approach for learning directed acyclic graph using MCMC algorithm:**

This paper's abstract describes how Directed Acyclic Graphs (DAGs) are trained using Markov Chain Carlo (MCMC) techniques. Furthermore, the emphasis here is on using discrete variables and restricting the space of the graphs whenever possible, which is viewed as Bayes' Paradigm. This L-1 Regularized MARKOV Blanket was used to accomplish this. The MCMC technique is then used to elaborate on the structures of complex DAG frameworks in the introductory section. The Markov chain was utilized as the algorithm, and there were a few concerns that were handled by applying the node ordering technique to smoothen the sample space. According to this research, after improving the structure of MCMC with blanket resampling, this strategy surpassed all the discussed techniques. All of this adds to the processing cost; therefore, the goal of this study is already described in the first paragraph, and to limit the space of potential graphs, which is essentially a Bayes' Paradigm. The EB technique is then utilized to explain the consistency of the graph and to constrain the search space, which is the core idea of the emphasis of this research. The DAG learning equation is like the Bayes Theorem Equation. The prior specification, a methodology related to prior probability, is explained further below.

In L1 Regularized Markov Blanket, each node is regressed over the others using L1 variable selection, which first learns a dependency network, then prunes edges, and lastly utilizes DAG search for score optimization. The following line contains the calculating formula. Multinomial Logistic Regression is utilized to solve a part of the equation, and k-fold cross-validation is used to tune the parameter. Following that, the paper discusses the introduction of a new criterion in which the estimation of a candidate x and y are causes for each other. According to the child's example, multinomial probability density functions (MPDFs) will differ substantially with the correct reason rather than the incorrect cause. The MPDFs' calculation and expanded or supporting calculation are shown below. Finally, the pairwise comparisons explain both the Lemma Likelihood function and the Lagrange Multiplier. Following that is the MCMC algorithm, which employs the Metropolis-Hastings sampler to move the DAGs, implying that at each step of the MC, one candidate graph will be replaced by the current graph by selecting the least value to minimize the search space. So, the key goal here is to focus on the added and removed edges while ignoring the reversed edges and then apply the burn-in graph mode to get a better graph.

Following that, the paper discusses the authors' suggested approach, in which there is a list of causes for each variable, and they are supplied as inputs to the MCMC algorithm. The Pseudo code and experimental findings, which include the networks Hailfinder, hepar2, Pathfinder, ALARM, Andes, and CAR DAGs, are a continuation of that. Each DAG has a distinct purpose. The correctness of the DAGs is listed on the following page. On the following page, we can see from the accuracy chart that Andes DAG is a better tutoring system with 223 variables and 338 edges after being evaluated with 20000 data samples. Correct edges, missing edges, and reverse edges are discussed, as well as how to achieve DAG accuracy results. Finally, they have demonstrated that not applying their new criterion for their findings has reduced accuracy.

**Making social networks more human: A topological approach:**

This research discusses social network analysis, where it is difficult to recognize nonhuman interactions. They have also offered a new topological way to identify violators utilizing Dunbar-inspired bounds. The abstract use Twitter as an example of removing violator-to-violator edges. In the introduction, key network qualities are highlighted, claiming that networks in repositories such as SNAP and the Laboratory for Web Algorithms lack these properties. According to the author, simply having topology nodes and edges is insufficient for test sets for many human-network algorithms; therefore, this study also discusses novel structural qualities that may help to justify which model is preferable for social network analysis. Because these networks have numerous nodes and edges, they should be able to use the structure to work more efficiently and quickly. After reading, I believe this research focuses on eradicating non-human behavior from social networks. The first paragraph in the following section of the structure of social networks and human limits is about using Dunbar's study, in which he states that electronic numbers do not change the strength of social relationships and that if a human wants to connect emotionally, it requires personal attention and time. The explanation of the Triadic closure property on how the connections between the nodes are strong or weak follows.

The part on nonhuman behavior in electronic social networks examines how corporations use giants like Twitter and Facebook to increase their ranking by influencing connections; the extended paragraph has already been understood in the first paragraphs. The paper describes utilizing the strength Index as a vertex attribute in the result summary sections to detect group activity where non-human behavior is involved. The definition of edge strength, a new structural attribute used to provide weights to unweighted graphs, is then continued. The discourse in the next paragraphs explains the equations and states that the h-index should be around 100. The explanation of the strength plots follows. It was discovered that some vertices have a significantly higher aggregate edge strength, indicating that they are likely to be part of the network's nonhuman component. According to their premise, the symmetric strength component should be in the range of S for the approach to be effective. It is also considered that reciprocating edges indicate increased human social connection. Then there's the strength index, which helps identify the real, important relationships. The strength index data can be modeled and fitted to the data of all social networks, with Twitter being a good fit. In continuation, the strength index is utilized to classify violators and non-violators, as previously indicated. Looking at the graph, there is a green line in the first figure that is splitting the data points, the points above the curve are strength index violators that were detected in this article by putting the Dunbar limit at 99.85th percentile. The explanation of the additional graphs on categorizing who is a violator and who is not following.

Cleaning has had an effect on two Graph properties: Page Rank and clustering coefficients. According to the paper's possible impact, there are algorithms designed to leverage social network features. Similarly, if non-human behavior influences structural qualities, it will also influence algorithm and code performance. It is claimed in the PageRank section that malicious subnetworks devised a method to artificially enhance the PageRank's relevance. The section Clustering Coefficients justifies how BTER is used to construct graphs. Now comes the Ground truth comparison portion, where content polluters are commonly denoted by honeypots or decoys classed as real users and total bots by using the Botometer, which has a 95% accuracy rate. They found around 20000 violators of which 8000 were still active based on the TAM dataset. Botometer scores on TAM content polluters were computed using the cumulative distribution function. The confusion matrix is then used to explain why 33 violators were misclassified as valid. Botometer also received a score of more than 0.5, indicating that the cleaning procedure is significantly reducing connections, implying that a validation phase was also completed. Following that comes an explanation of the pairwise distribution of similar subsequence lengths. Now comes the development of two more cleaning methods. The first step is to identify outliers based on the basic attributes mentioned earlier in the paper, such as the clustering coefficient, PageRank, and so on. The second step is to use different edge-strength measures S, followed by formulae related to the Easley-Kleinberg measure. They referenced researchers and firms working on social-network data in collusion remarks, which sounds fascinating to me; if given the opportunity, I'd like to study the dataset. They also stated that non-human behavior data existed in Twitter networks and that the cleaning methods they employed had an impact on making the algorithms work better. The strength index is still a work in progress, with the purpose of improving the efficiency of graph algorithms.

**Parameter inference with deep jointly informed neural networks:**

The problem in this research is simulating inertial confinement fusion (ICF) experiments since many of the simulation inputs are unknown and unmeasurable. Post-Shot Analysis is a term used to define a collection of simulation inputs that result in consistent outcomes. To train inverse models like this, neural network models are typically utilized; employing MCMC sampling for these types of tasks is typically costly. Following on from the introduction, the purpose of ICF is to spark fusion reactions by compressing deuterium-tritium DT to high temperatures. Because such tests are costly, designers typically rely primarily on simulations. However, because these simulations cannot be controlled or quantified, they must be validated empirically; this procedure is known as post-shot analysis. This type of analysis takes time because it requires a lot of manual input simulation and reaching conclusions with only one single post-shot solution can result in wrong data interpretation. To address this issue, our article used a neural network-based technique.

The Deep Jointly Informed Neural Network (DJINN) part discusses how ICF simulations are expensive, and MCMC sampling is not an option, so surrogate models have been employed to span the parameter of interest. Initially, such models are linear regression or power law models, but as the data grows larger, more advanced ML methods, such as a Deep neural network, are required. As previously stated, neural networks necessitate hyperparameter methodologies and rules. DJINN is an ensembled approach that maps a random forest of decision trees into an ensemble of Neural networks, which can be used to boost efficiency and accuracy. Dropout is one way for preventing algorithm overfitting, which requires removing a small group of neurons from the network. This algorithm acts similarly to Gaussian process methods. DJINN's performance is compared to Bayesian multivariate adaptive regression (BMARS), Bayesian additive regression trees (BART), and Gaussian processes (GP). The datasets are then produced for comparison using the logistic function and Gaussian distributed noise. The parameters utilized are then described, as are the metrics used to quantify the accuracy in the two tables, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Explained Variance Ratio (EV). Following all of this, B-DJINN with dropout comes out to be more efficient than other models such as BMARS and BART. Inverse models using B-DJINN that are trained directly from output to input space are preferable over forward models that are sampled using MCMC. To reduce prediction uncertainty in B-DJINN, multiple observables in the output space are required.

For the logistic function dataset, parameter inference using inverse models employs MCMC sampling with B-DJINN and GP models. The graphs on top show the B-DJINN, GP, Inverse, and true K values, and the MCMC sampled DJINN model offered the most accurate precise prediction for k. According to the graph, k=9 was the optimal starting point for sampling. Inverse models can also be constructed using other Bayesian surrogates such as GP, BART, or BMARS. However, B-DJINN is the preferable surrogate choice since it has greater predictive performance with less hyperparameter tweaking and can be trained faster than models that require MCMC sampling. The following section of the study explains how ICF post-shot analysis is experimented with utilizing Inverse models and how it performs with neural networks. We can go over the distribution charts in the paper to have a better understanding of this. Furthermore, it is stated that autoencoder neural networks are utilized to compress multiple observables to the lowest representation of data. When compared to MCMC sampling, this is far superior.