Course: CSC 696H SP24 001

Assignment: Critical Reading Summaries

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1. Topic: Inference: Approximate Bayesian Computation
   Reading: Inference: Approximate Bayesian Computation

   Summary: The reading talks about the statistical inference-based model and the attributes with Bayes theorem in the centre of discussion. The paper explains the Bayes theorem and talk about the ABC Rejection Algorithm to explains (under the heading "Summary statistics") the use of summary statistics to reduce the dimensionality of the observed and simulated data while retaining the key information required for inference.

   As someone who knows about statistics but not in depth, it gives me a rough idea about how the statistical models can be used to decide the validity of the data in light of prior knowledge.

2. Topic: Inference Bayesian Conditional Density Estimation
   Reading: Fast ε-free Inference of Simulation Models with Bayesian Conditional Density Estimation

   Summary: The reading talk about estimation of conditional probability distribution (Bayesian Conditional Density) can done directly from data. Free from using the simulation-based models where likelihood computation, either is not possible or it is very computationally expensive, the likelihood is not used to establish the posterior inference that models the relationship between parameter and the observation.

   The experiments show the MDN (Mixed Density Network) -based approaches and their potential for broader applications in likelihood-free inference. The paper concludes that the BCDE is a valuable tool that can help avoid likelihood inference. It is efficient and can be more precise to let go approximation.

3. Topic: Bayesian Deep Learning: Introduction
   Reading: Weight Uncertainty in Neural Networks

   Summary: The reading talk about a new algorithm called Bayes by Backprop for learning a probability distribution on the weights of a neural network. It provides a principled way to incorporate uncertainty into Neural Network. This is done by learning the probability distribution over the weights that represent their uncertainty given the observed data.

   The paper provides experimental results using more than one type of problems like Classification, Regression and Bandit Problems to show the outcome in terms of accuracy, uncertainty quantification or efficiency

4. Topic: Bayesian Deep Learning: Monte Carlo Dropout
   Reading: Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning

   Summary: The reading is about casting dropout training in deep neural networks as approximate Bayesian inference in deep Gaussian process. It mitigates the problem of representing uncertainty in deep learning without sacrificing computational complexity or test accuracy. The paper explains the research done in this context to demonstrate the uncertainty estimates for the dropout NNS.

   The model uncertainty in regression and classification task are also presented when dropout is used in such cases, suggesting that the dropout can be used to quantify the model uncertainty.

5. Topic: Bayesian Deep Learning: Variational Dropout
   Reading: Variational Dropout and the Local Reparameterization Trick

   Summary: The Reading is about how the Dropout can be used in Gaussian inference with a possibility to improve variational Bayesian inference on the parameters of the model. The paper explains the possibility of relationship between global uncertainty and uncertainty locally to sample, this leads to a possibility for application of local reparameterization.

   The paper suggests a variational dropout, where the dropout rate can be learned from the very input data itself, can used with local reparameterization to improve the performance of the model.

6. Topic: Bayesian Deep Learning: Information Bottleneck
   Reading: Deep Variational information Bottleneck

   Summary: The reading is about application of Variational information bottleneck, where the goal is to learn efficient and task-relevant representation of data by balancing the compression and relevance. The paper talks about parameterizing the information bottleneck using Neural Network and use reparameterization trick to get improved performance in generalization.
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7. Topic: Bayesian Deep Learning: Representation Learning
   Reading: Interpretable Representation Learning by Information Maximizing

   Summary: The reading is about InfoGAN an extension of Generative Adversarial Networks (GAN), designed to learn interpretable and disentangled representations in unsupervised manger. The paper suggests that this can be done by maximizing the mutual information between latent variables and the generated data. This enables meaningful control over specific data attributes.

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8. Topic: Bayesian Deep Learning: Representation Learning
   Reading: Information Dropout: Learning Optimal Representations Through Noisy Computation

   Summary: The reading is about a regularization technique call information dropout. The said technique is based on the principles of dropout, information theory and the variational inference. The paper suggests that the multiplicative noise injection improves the regularization of model and enhances the learning of optimal disenabled representation.

9. Topic: Generative Model: Variational Autoencoder
   Reading: Auto-encoding Variational Bayes.

   Summary: The reading is about using variational inference in neural network for learning high-dimensional data. The primary contribution involves taking advantage of reparameterization trick for efficient gradient based optimization. The paper suggests that with reparameterization training efficiency of generative model can be improved.

10. Topic: Generative Model: Diffusion Probabilistic Models
    Reading: Denoising Diffusion Probabilistic Models.

    Summary: The reading is about Denoising Diffusion Probabilistic Model as a robust approach for generative modelling. The paper suggests that DDPM can be used to achieve start of the art outcomes in unsupervised image synthesis and can be useful for data compression, especially for high resolution images to be used on internet.

11. Topic: Generative Model: Diffusion implicit Models
    Reading: Denoising Diffusion Implicit Models.

    Summary: The reading is about a comparing Denoising Diffusion probabilistic model (DDPM) that has achievement of high quality image generation , with Denoising Diffusion Implicit model (DDIM) which are claimed to be more deterministic and efficient alternative. The paper claims that DDIM can achieve faster sampling while not compromising on the high-quality generative performance. The DDIM is said to provide significant improvements in efficiency and interpretability of diffusion based generative models, an alternative with both speed and quality in sample generation.

12. Topic: Generative Model: Score-Based Generative Modelling
    Reading: Score-Based Generative Modelling Through Stochastic Differential Equations.

    Summary: The reading is about Score-Based Generative modelling (SBGM) that uses Stochastic differential equation to transform data distribution into noise and then back to data. The process used Score matching with Langevin dynamics (SMLD) and Denoising diffusion probabilistic modelling (DDPM) together to extend them with new capabilities and efficiencies. The paper claims to have offered these improved generative capabilities as a contribution to the field of probabilistic modelling.

13. Topic: Generative Model: Energy-Based Models
    Reading: Implicit Generation Modelling with Energy-Based Models

    Summary: The reading is about use of Energy-Based Models (EBM) as framework for generative modelling. The MCMC (Markov Chain Monte Carlo) based EBM when scaled are successful on high-dimensional data and robotic trajectories.

    The paper claims that the EBM can generalize the combination of shape and position, and this compositional nature of EBM is crucial to generalize in Zero-Shot cross product Generalization task, where model can correctly predict or generate output without having seen the combination during the training.

14. Topic: Generative Model: Energy-Based Models
    Reading: How to train your Energy-Based Models

    Summary: The reading is about Energy Based Models (EBM). The paper reviews some of the latest approaches for EBM training, like Maximum likelihood Training with MCMC, Score Matching (SM), Noise Contrastive Estimation (NCE), KL Divergence Minimization, Stein Discrepancy and Adversarial Training.

15. Topic: Uncertainty Quantification: Variational BOED
    Reading: Variational Bayesian Optimal Experimental Design

    Summary: The reading is about the challenge of Bayesian optimal experimental design (BOED) framework that is conventionally used for designing experiments with a goal to maximize the information gain. The information gain is commonly measured on metrics of "Expected Information Gain" (EIG) with quantifies the reduction in uncertainty.

    The paper introduces variational methods for efficiently estimating the EIG overcoming computational bottleneck and enabling real time and sequential experimental designs.

16. Topic: Uncertainty Quantification: Variational MI Bounds
    Reading: On Variational Bounds of Mutual Information

    Summary: The reading is about estimation and optimization of Mutual Information (MI) that is used to quantify the dependency between two variables. Estimating MI is challenging in high dimensions, specifically with limited samples.

    The paper review existing variational bounds for MI, introduces new ones and provides empirical analyses to evaluate their trade off between bias and variance.

17. Topic: Uncertainty Quantification: MINE
    Reading: Mutual Information Neural Estimation

    Summary: The reading is about Mutual Information Neural Estimator (MINE), a scalable and efficient method to estimate Mutual Information (MI) between continuous random variables using neural networks.

    The paper demonstrates MINE's utility across various applications, that includes generative modelling and information bottleneck methods. The efficiency of this estimator is demonstrated with application in multiple settings.

18. Topic: Uncertainty Quantification: DAD
    Reading: Deep Adaptive Design: Amortizing Sequential BOED

    Summary: The reading is about Deep Adaptive Design (DAD), this is a novel method of adaptive experimentation that focuses on learning a design policy network offline. This method eliminates the traditional sequential Bayesian Optimal Experimental Design (BOED), allowing rapid decision-making during the live experiment.

    The paper talks about the conventional BOED approach and how DAD performed significantly better using amortization and shows competitive performance even in absence of amortization.

19. Topic: Uncertainty Quantification: Contrastive Predictive Coding
    Reading: Representation Learning with Contrastive Predictive Coding

    Summary: The reading is about Contrastive Predictive Coding (CPC), this is a framework for unsupervised representation learning across various data modalities, like audio, vision , NLP and reinforcement learning. This approach combines contrastive learning with predictive coding to extract representations that captures high-level features while discarding noise and irrelevant details.

    The paper demonstrates how useful is this framework, while being simple and consuming low resource for training.

20. Topic: Uncertainty Quantification: Bayesian
    Reading: Modern Bayesian Experimental Design

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