Course Project Details

The aim of the project is to acclimate you to the process of conducting research in statistical modeling or machine learning: 1) tackle an intimidatingly general problem 2) narrow the scope to a specific set of parameters to study 3) replicate existing literature studying these parameters and 4) innovate on top of existing work incrementally.

Due: December 19th, 11:59pm

Grading: Your grade is based on:

1. How well your deliverable satisfies the project specifications (described below)
2. Your progress leading up to the final deliverable. There will be a series of check points with your project TF and instructor through out the semester. Your final grade will account for how much progress you've made by each check point.

Instructions:

- **Team:** Form a team of 2-4 people
- **Topic:** Choose a paper from the approved list of papers (we are limiting 2 teams per paper, on a first-come-first-serve basis). You may propose a paper, but it must be approved by your instructor.
- **Mentoring:** You will have a designated TF for your project and you are welcomed to schedule meetings between your team and the instructor.
- **Project deliverable:** A well-formatted Jupyter notebook (optimized for readability) containing:
  - **Clear exposition of :**
    - Problem statement - what is the problem the paper aims to solve?
    - Context/scope - why is this problem important or interesting?
    - Existing work - what has been done in literature?
    - Contribution - what is gap in literature that the paper is trying to fill? What is the unique contribution
    - Technical content (high level) - what are the high level ideas behind their technical contribution
    - Technical content (details) - ***highlight (not copy and paste entire sections)*** the relevant details that are important to focus on (e.g. if there's a model, define it; if there is a theorem, state it and explain why it's important, etc).
    - Experiments - which types of experiments were performed? What claims were these experiments trying to prove? Did the results prove the claims?
    - Evaluation (your opinion) - do you think the work is technically sound? Do you think the proposed model/inference method is practical to use on real data and tasks? Do you think the experimental section was strong (there are sufficient evidence to support the claims and eliminate confounding factors)?
    - ***Future work (for those interested in continuing research in a related field)*** - do you think you can suggest a concrete change or modification that would improve the existing solution(s) to the problem of interest? Try to implement some of these changes/modifications.

  Your exposition should focus on summarization and highlighting (aiming for an audience of peers who have taken AM207). There is no point rewording the paper itself. Organize and explain the ideas in a way that makes sense to you, that features the most salient/important aspects of the paper, that demonstrates understanding and synthesis.

- **Code:**
  - At least one clear working pedagogical example demonstrating the problem the paper is claiming to solve.
  - At lease a bare bones implementation of the model/algorithm/solution (in some cases, you may be able to make assumptions to simplify the model/algorithm/solution with the approval of your instructor)
  - Demonstration on at least one instance that your implementation solves the problem.
  - Demonstration on at least one instance the failure mode of the model/algorithm/solution, with an explanation for why failure occurred (is the dataset too large? Did you choose a bad hyper parameter?). The point of this is to point out edge cases to the user.

You are welcome to study any code that is provided with the paper, you are however not allowed to copy code. Your implementation must be your own. If a public repo is available for your paper, you are encouraged to first try reproducing some results using the authors code -- this will give you an idea of how their algorithm/model works.

List of Pre-Approved Papers:

1. Black-Box Alpha Divergence
2. Variational Inference with Normalizing Flows
3. Stein Variational Gradient Descent
4. Neutralizing Bad Geometry in HMC Using Neural Transport
5. Slice Sampling
6. Iterative Amortized Inference
7. Proximity Variational Inference
8. InfoVAE: Balancing Learning and Inference in Variational Autoencoders
9. Stochastic Gradient Hamiltonian Monte Carlo
10. Amortized Inference Regularization
11. Reparametrization Gradients Through Acceptance-Rejection Sampling Algorithms
12. Grammar VAE's
13. Learning Latent Subspaces in VAE's
14. Discretely Relaxing Continuous Variables for Tractable Variational Inference
15. Multimodal Generative Models for Scalable Weakly-Supervised Learning
16. Accurate Uncertainties for Deap Learning Using Calibrated Regression
17. Hierarchical Implicit Models and Likelihood Free Variational Inference
18. Semi-Separable HMC for Inference in Bayesian Hiearchical Models
19. The Variational Hierarchical EM Aglorithm for Clustering HMM's
20. Forward-Backward Activation Algorithm for Hierarchical Hidden Markov Models
21. A Collapsed Variational Bayesian Inference Algorithm for LDA
22. Predictive Uncertainty Estimation via Prior Networks
23. Informational Constraints on Auto-encoding Variational Bayes
24. Improving Explorability in Variational Inference with Annealed Variational Objectives
25. Topics over Time: A Non-Markov Continuous-Time Model of Topical Trends
26. What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?
27. Subspace Inference for Bayesian Deep Learning