CS698X: Topics In Probabilistic Modeling And Inference
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Quiz 3

Q.1 When estimating the hyperparameters of a probabilistic model using MLE-II and EM, do you expect both approaches to give the same solution in general? If yes, why? If no, why not?

Max. score: 3; Neg. score: 0; Your score: 1

Your answer:

No both the approaches do not give the same solution. In MLE-II we choose hyperparms that best describe the marginal likelihod that are unique. where as the in EM is sensitive to the initialization and can get different values.

Feedback:

Q.2 Suppose we want to estimate all the unknowns of a Bayesian linear regression model. Will using online EM or stochastic VI be better (faster) than their batch counterparts (batch EM and batch VI)}? If yes, why? If no, why not?

Max. score: 3; Neg. score: 0; Your score: 0

Your answer:

Feedback:

Q.3 For which of these methods, the idea of Monte-Carlo approximation an expectation is/can be used?

Max. score: 2; Neg. score: 0; Your score: 0

- [x] Importance Sampling
- [ ] Black-box VI
- [x] Reparametrization trick based VI
- [x] Expectation Maximization

Q.4 In order to apply MCMC to infer a posterior distribution p(z|x) which of the following conditions are needed?

Max. score: 2; Neg. score: 0; Your score: 0

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- [x] ✔ It should be possible to evaluate the posterior up to a proportionality constant for any z
- [ ] The model should at least have local conjugacy

Q.5 Which of these methods are designed to handle the issue of intractable ELBO or its derivatives?

Max. score: 2; Neg. score: 0; Your score: 0

- [x] ✔ Reparametrization Trick based VI
- [x] Mean-field VI
- [ ] ✔ Black-box VI
- [x] Amortized VI

Q.6 In a latent variable model, when doing hybrid inference, how do we usually decide which unknowns to do point estimate on and for which unknowns to infer the posterior? If you want, you may answer this question using an example of a probabilistic model of your choice.

Max. score: 3; Neg. score: 0; Your score: 3

Your answer:

In this we consider the local variables for inference and global variables for point extimate.

In cluster assignment mixture example z_n for inference and (\theta,\phi) for point estimate

Feedback:

Q.7 Suppose you are using MH sampling to infer the posterior distribution of some model. Does the MH acceptance probability depend on the number of observations? If yes, why? If no, why not?

Max. score: 3; Neg. score: 0; Your score: 0

Your answer:

Yes the MH acceptance probablity dependens on the no of oberservations. As the observations increases the accpetance probability increases as the points go towards the heigher probability region.

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computing the posterior predictive distribution depend on the number of samples? If yes, why? If no, why not?

Max. score: 3; Neg. score: 0; Your score: 3

Your answer:

yes the cost depends on the number of samples as we need to average the posterior distribution over all the samples we have to get PPD.

Feedback:

Q.9 For a Gaussian mixture model, which unknowns are global and which ones are local?

Max. score: 3; Neg. score: 0; Your score: 0

Your answer:

Feedback:

Q.10 Which of these algorithms can be used to learn the posterior (or conditional posterior) distribution for the weight vector of a logistic regression model (assume no changes to the original model, such as no additional variables introduced)?

Max. score: 2; Neg. score: 0; Your score: 0

- [x] Expectation Maximization
- ✔ [ ] Metropolis-Hastings
- [x] Standard Gibbs sampling
- ✔ [ ] SGLD

Q.11 Which of the following are true for Variational Inference (VI)?

Max. score: 2; Neg. score: 0; Your score: 0

- ✔ [ ] It learns a variational approximation q(Z) with a high entropy
- ✔ [x] Always converges

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Q.12 Which of these are MCMC algorithms?

Max. score: 2; Neg. score: 0; Your score: 2

- ✔ [x] Metropolis algorithm
- [ ] Rejection Sampling
- ✔ [x] Gibbs sampling
- ✔ [x] Metropolis Hastings algorithm

Q.13 Which of the following is/are true about the EM algorithm?

Max. score: 2; Neg. score: 0; Your score: 2

- [ ] Only applicable when prior and likelihood are in exponential family
- ✔ [x] Always converges
- ✔ [x] Sensitive to initialization
- [ ] Gives only point estimates for all unknowns

Q.14 When using a VI based approximation of a posterior distribution, is the posterior predictive distribution always available in closed form? If yes, why? If no, why not?

Max. score: 3; Neg. score: 0; Your score: 2

Your answer:

No, as sometimes the posterior itself wont be in closed form which intern do not yeild closed form for PPD.

Feedback:

Score: 13