Advanced Probabilistic Machine Learning and Applications: Exam (29-09-2021)

1 Exercise 1: Variational inference and topic modeling

- 1. What is the main idea of Variational Inference (VI)?
- 2. How is this different than Gibbs sampling?
- 3. Describe the Latent Dirichlet Allocation (LDA) for topic modeling. In particular, i) describe what are the variables involved and what is the main idea of the model; ii) write the generative process drawing the various variables: β_k (word proportion), θ_d (topic proportion), z_{dn} (topic assignment) and w_{dn} (word).
- 4. Describe Mean Field Variational approximation for the LDA and describe what would be the variational distributions for the latent variables.
- 5. Consider the variational distributions proposed in the previous question. Are these the optimal ones? Discuss about this.
- 6. What are the main assumptions and possible limits of LDA?
- 7. Describe the CAVI (coordinate ascent VI) procedure.

2 Exercise 2: matrix factorization

- 1. Describe Poisson matrix factorization and its main assumptions. It can help to start by defining what the data A, a matrix with entries A_{ij} , can represent in example applications.
- 2. State various inference approaches and estimation methods that can be used to infer the parameters. Mention their differences and similarities (if any).
- 3. One main parameter is the affinity matrix with entries c_{kq} . Derive the Maximum Likelihood estimate \hat{c}_{kq} of this. Hint: write the Poisson likelihood and use Jensen's inequality with a variational distribution q_{ijkq} .
- 4. Describe possible constraints on the parameters and connections with regularization.
- 5. Consider now matrix factorization (not the Poisson one). How does this differ from the Poisson case described above?
- 6. Describe possible approaches to tackle matrix factorization and their connections (if any).
- 7. (extra) What could be possible problems of the basic approaches? How would you address it?.

¹A Poisson distribution for a variable *x* and parameter λ is $P(x|\lambda) = e^{-\lambda} \lambda^x / x!$.

 $^{^{2}\}log(\sum_{k}x_{k}) \ge \sum_{k}q_{k}\log\frac{x_{k}}{q_{k}}$, where q_{k} are any probabilities satisfying $\sum_{k}q_{k}=1$ and x_{k} are any set of positive numbers.