CS181 Topics for Midterm Two

Sasha Rush and David C. Parkes

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The best way to prepare for the midterm is to review the lecture slides, the theory psets, section notes, and the example midterm questions. Make sure that you understand the most important concepts. These are generally the topics that are covered in detail in lecture.

The midterm will be both conceptual and analytical, testing ideas and understanding, and will not involve writing pseudocode. *The midterm is non-cumulative* (except where we built on concepts later in the semester), and covers material on clustering from Lecture 12 (3/7) up to reinforcement learning from Lecture 21 (4/13). The lecture on RL will continue on 4/18. This lecture will also cover new content on deep RL, but this material will not be tested. The material in the lecture on 'deep learning for text' will NOT be tested.

You should not try to memorize complicated formulas such as the PDF for a Gaussian distribution or Beta distribution, or complicated matrix cookbook rules, but you should be familiar with probability theory and the various models and methodologies we've studied in this course. Rather than memorize equations for things such as value iteration, Q-learning, or the recurrence for forward-backward in HMMs, we suggest that you are familiar enough that you would be able to work with them if provided with reminders.

Here is a brief list of topics that you could expect to be asked about. This list emphasizes the main focus areas and is not fully inclusive.

- *Clustering*:
  - Know the K-means objective, know Lloyd's algorithm, know hierarchical agglomerative clustering, know dendrograms. Understand the typical kinds of applications of clustering.
- *Mixture models*:
  - Understand how to work with the Gaussian mixture model, the mixture of multinominal, and the topic model (no need to memorize their specific forms).
  - Expectation maximization: understand expected complete-data likelihood, the E-step and the M-step, and relationship to the MLE problem. (Know how to use EM, but no need to memorize specific algebraic forms of solutions to the E-step or M-step for particular models).
  - Understand the typical kinds of applications of mixture models.
- *Directed graphical models*:
  - Understand latent vs observed variables, handling parameters as random variables, and the plate notation.

- *Dimensionality reduction and PCA*:
  - Understand motivations, typical applications; understand the PCA loss function (no need to memorize); understand the visual, and and encoding and reconstruction interpretation of PCA
  - Know how to use eigenvectors on empirical covariance for PCA (but don't memorize)
  - (Out of scope: the prob. interpretation of PCA, the kernel PCA, and the idea of autoencoders.)
- *Hidden Markov Models:*
  - Know the form of the HMM, the distribution it defines, the conditional indpendence properties, and understand the typical kinds of applications.
  - Learning: complete-information version, use of EM (no need to memorize the E or M step rules).
  - Understand the inference questions of interest, the forward-backward algorithm (no need to memorize the α- and β definitions), the Viterbi algorithm (no need to memorize the recurrence), and how to use α and β values for inference.
- *Bayesian Networks*:
  - Understand the distribution defined by a Bayesian network (BN), the role of topological orderings, local conditional independence properties, and typical applications. Know the rules of d-separation, and how to reason about conditional independence.
  - Can construct a BN for a given variable ordering, understand the effect of different orderings, and how to learn parameters complete data and known structure (incomplete data, unknown structure out of scope)
  - Know how to use variable elimination for exact inference, and understand the use of leaves-first ordering for polytrees and the importance of a good elimination order. Motivations for approximate inference, understand MCMC/Gibbs sampling (and Markov blanket), and why Gibbs sampling is more efficient than rejection sampling.
  - (Out of scope: Variational methods, undirected graphical models such as MRFs and factor graphs.)
- *Markov Decision Processes*:
  - Know the form of the MDP model, can model problems via MDPs, understand the typical kinds of applications of MDPs
  - Finite horizon planning: understand the planning objective, the MDP value function, policy evaluation, and the use of value iteration for planning. No need to memorize formulas.
  - Infinite horizon: understand the planning objective, the MDP value function, policy evaluation, Bellman equations, value iteration (VI), policy iteration (PI) and how VI and PI compare. No need to memorize formulas.
  - (Out of scope: specifics of any particular gridworld model, expectimax.)

- *Reinforcement Learning*:
  - Understand typical applications, exploration vs exploitation, and the difference between model-based vs model-free learning.
  - Understand the Q-function, the alternate form of Bellman equations, and the idea of SGD for temporal difference learning. No need to memorize formulas.
  - Understand the structure of an TD-RL algorithm, the use of epsilon-greedy, and the difference between SARSA and Q-learning. No need to memorize formulas.
  - Understand how to handle large state and action spaces via basis functions