## LIGN 165 Problem Set 4

Please put your answers into a file called lastname-firstname.clj. Be careful to follow the instructions exactly and be sure that all of your function definitions use the precise names, number of inputs and input types, and output types as requested in each question. If you do not follow these instructions, we cannot give you credit for your answer.

For running your code, you have two options. You can run your code on the course website. Alternatively, you can install Clojure on your local machine and write and debug the answers to each problem in a local copy of lastname-firstname.clj. You can find information about installing and using Clojure here https://clojure.org/.

You may collaborate with up to three other students on this problem set. You must submit your work individually. If you do not submit a copy of the problem set under your own name, you will not get credit. When you submit your work, you must indicate who you worked with, and what each of your individual contributions were.

**Problem 1:** In this problem set, we are going to be considering a variant on the hierarchical bag-of-words model that we looked at in class.

We will be looking at a simple prior distribution over the parameters  $\theta$ . The probability distribution is defined in the code below:

```
(def vocabulary '(call me ishmael))

(def theta1 (list (/ 1 2 ) (/ 1 4 ) (/ 1 4 )))
(def theta2 (list (/ 1 4 ) (/ 1 2 ) (/ 1 4 )))

(def thetas (list theta1 theta2))

(def theta-prior (list (/ 1 2) (/ 1 2)))
```

Our vocabulary in this case consists of three words. Each value of  $\theta$  therefore defines a bag of words distribution over sentences containing these three words. The first value of  $\theta$  (theta1) assigns  $\frac{1}{2}$  probability to the word 'call,  $\frac{1}{4}$  to 'me, and  $\frac{1}{4}$  to 'ishmael. The second value of  $\theta$  (theta2) assigns  $\frac{1}{2}$  probability to 'me, and  $\frac{1}{4}$  to each of the other two words. The two values of  $\theta$  each have prior probability of  $\frac{1}{2}$ . Assume throughout the problem set that the vocabulary and possible values of  $\theta$  are fixed to these values above.

In addition to the code defining the prior distribution over  $\theta$ , we will be using some helper functions defined in class:

```
(if (empty? lst)
    base
     (f (first lst)
       (list-foldr f base (rest lst)))))
(defn log2 [n]
 (/ (Math/log n) (Math/log 2)))
(defn score-BOW-sentence [sen probabilities]
 (list-foldr
  (fn [word rest-score]
    (+ (log2 (score-categorical word vocabulary probabilities))
      rest-score))
  0
  sen))
(defn score-corpus [corpus probabilities]
 (list-foldr
  (fn [sen rst]
    (+ (score-BOW-sentence sen probabilities) rst))
  corpus))
(defn logsumexp [log-vals]
 (let [mx (apply max log-vals)]
   (+ mx
     (log2
        (apply +
              (map (fn [z] (Math/pow 2 z))
                  (map (fn [x] (- x mx)) log-vals)))))))
```

Recall that the function score-corpus is used to compute the log probability of a corpus given a particular value of the parameters  $\theta$ . Also recall (from the Discrete Random Variables module) the purpose of the function logsumexp, which is used to compute the sum of (log) probabilities; you should return to the lecture notes if you don't remember what this function is doing. (Note that the version of logsumexp here differs slightly from the lecture notes, as it does not use the & notation.)

Our initial corpus will consist of two sentences:

Write a function theta-corpus-joint, which takes three arguments: theta, corpus, and theta-probs. The argument theta is a value of the model parameters  $\theta$ , and the argument corpus is a list of sentences. The argument theta-probs is a prior probability distribution over the values of  $\theta$ . The function should return the log of the joint probability  $Pr(C = corpus, \theta = theta)$ .

Use the chain-rule identity discussed in class:  $\Pr(C, \theta) = \Pr(C|\theta) \Pr(\theta)$ . Assume that the prior distribution  $\Pr(\theta)$  is defined by the probabilities in theta-probs.

After defining this function, call (theta-corpus-joint theta1 my-corpus theta-prior). This will compute (the log of) the joint probability of the model parameters theta1 and the corpus my-corpus.

**Problem 2:** Write a function compute-marginal, which takes two arguments: corpus and theta-probs. The argument corpus is a list of sentences, and the argument theta-probs is a prior probability distribution on values of  $\theta$ . The function should return the  $\log$  of the marginal likelihood of the corpus, when the prior

distribution on  $\theta$  is given by theta-probs. That is, the function should return  $\sum_{\theta \in \Theta} \Pr(\mathbf{C} = \mathsf{corpus}, \Theta = \theta)$ .

Hint: Use the logsumexp function defined above.

After defining compute-marginal, call (compute-marginal my-corpus theta-prior). This will compute the marginal likelihood of my-corpus (which was defined above), given the prior distribution theta-prior.

**Problem 3:** Write a procedure compute-conditional-prob, which takes three arguments: theta, corpus, and theta-probs. The arguments have the same interpretation as in Problems 1 and 2. The function should return the log of the conditional probability of the parameter value theta, given the corpus. Remember that the conditional probability is defined by the equation:

$$\Pr(\Theta = \theta | \mathbf{C} = \text{corpus}) = \frac{\Pr(\mathbf{C} = \text{corpus}, \Theta = \theta)}{\sum_{\theta \in \Theta} \Pr(\mathbf{C} = \text{corpus}, \Theta = \theta)}$$
(1)

**Problem 4:** Write a function compute-conditional-dist, which takes two arguments: corpus and thetaprobs. For every value of  $\theta$  in thetas (i.e., theta1 and theta2), it should return the  $\log$  of the conditional probability of  $\theta$  given the corpus. That is, it should return a list of conditional probabilities of the different values of  $\theta$ .

**Problem 5:** Call (compute-conditional-dist my-corpus theta-prior). What do you notice about the conditional distribution over values of  $\theta$ ? Exponentiate the values you get back, so that you can see the regular probabilities, rather than just the log probabilities. Explain why the conditional distribution looks the way it does, with reference to the properties of my-corpus.

**Problem 6:** When you call compute-conditional-dist, you get back a probability distribution over values of  $\theta$  (the conditional distribution over  $\theta$  given an observed corpus). This is a probability distribution just like any other. In particular, it can be used as the prior distribution over values of  $\theta$  in a hierarchical bag of words model. Given this new hierarchical BOW model, we can do all of the things that we normally do with such a model. In particular, we can compute the marginal likelihood of a corpus under this model. This marginal likelihood is called a *posterior predictive distribution*.

Below we have defined the skeleton of a function compute-posterior-predictive. It takes three arguments: observed-corpus, new-corpus, and theta-probs. observed-corpus is a corpus which we observe, and use to compute a conditional distribution over values of  $\theta$ . Given this conditional distribution over  $\theta$ , we will then compute the marginal likelihood of the corpus new-corpus. The procedure compute-posterior-predictive should return the  $\log$  of the marginal likelihood of new-corpus given the conditional distribution on  $\theta$ .

(defn compute-posterior-predictive [observed-corpus new-corpus theta-probs] (let [conditional-dist ... (compute-marginal ...

Once you have implemented compute-posterior-predictive, call (compute-posterior-predictive my-corpus my-corpus theta-prior). What does this quantity represent? How does its value compare to the marginal likelihood that you computed in Problem 2?

**Problem 7:** In the previous problems, we have written code that will compute marginal and conditional distributions *exactly*, by enumerating over all possible values of  $\theta$ . In the next problems, we will develop an alternate approach to computing these distributions. Instead of computing these distributions exactly, we will approximate them using random sampling.

The following functions were defined in class, and will be useful for us going forward:

```
(defn normalize [params]
 (let [sum (apply + params)]
   (map (fn [x] (/ x sum)) params)))
(defn flip [weight]
 (if (< (rand 1) weight)
    true
    false))
(defn sample-categorical [outcomes params]
 (if (flip (first params))
    (first outcomes)
    (sample-categorical (rest outcomes)
                    (normalize (rest params)))))
(defn repeat [f n]
 (if (= n 0)
    '()
    (cons (f) (repeat f (- n 1)))))
(defn sample-BOW-sentence [len probabilities]
      (if (= len 0)
       '()
       (cons (sample-categorical vocabulary probabilities)
         (sample-BOW-sentence (- len 1) probabilities))))
```

Recall that the function sample-BOW-sentence samples a sentence from the bag of words model of length len, given the parameters theta.

Define a function sample-BOW-corpus, which takes three arguments: theta, sent-len, and corpus-len. The argument theta is a value of the model parameters  $\theta$ . The arguments sent-len and corpus-len are positive integers. The function should return a sample corpus from the bag of words model, given the model parameters theta. Each sentence should be of length sent-len and number of sentences in the corpus should be equal to corpus-len. For example, if sent-len equals 2 and corpus-len equals 2, then this function should return a list of 2 sentences, each consisting of 2 words.

Hint: Use sample-BOW-sentence and repeat.

**Problem 8:** Below we have defined the skeleton of the function sample-theta-corpus. This function takes three arguments: sent-len corpus-len and theta-probs. It returns a list with two elements: a value of  $\theta$  sampled from the distribution defined by theta-probs; and a corpus sampled from the bag of words model given the sampled  $\theta$ . (The number of sentences in the corpus should equal corpus-len, and each sentence should have sent-len words in it.)

We will call the return value of this function a theta-corpus pair.

(defn sample-theta-corpus [sent-len corpus-len theta-probs]

(let [theta ... (list theta ...

**Problem 9:** Below we have defined some useful functions for us. The function get-theta takes a theta-corpus pair, and returns the value of theta in it. The function get-corpus takes a theta-corpus pair, and returns its corpus value. The function sample-thetas-corpora samples multiple theta-corpus pairs, and returns a list of them. In particular, the number of samples it returns equals sample-size.

(defn get-theta [theta-corpus]
 (first theta-corpus))

(defn get-corpus [theta-corpus]
 (first (rest theta-corpus)))

(defn sample-thetas-corpora [sample-size sent-len corpus-len theta-probs] (repeat (fn [] (sample-theta-corpus sent-len corpus-len theta-probs)) sample-size))

We are now going to estimate the marginal likelihood of a corpus by using random sampling. Here is the general approach that we are going to use. We are going to sample some number (for example 1000) of theta-corpus pairs. These are 1000 samples from the joint distribution defined by the hierarchical bag of words model. We are then going to throw away the values of theta that we sampled; this will leave us with 1000 corpora sampled from our model.

We are going to use these 1000 sampled corpora to estimate the probability of a specific target corpus. The process here is simple. We just count the number of times that our target corpus appears in the 1000 sampled corpora. The ratio of the occurrences of the target corpus to the number of total corpora gives us an estimate of the target's probability.

More formally, let us suppose that we are given a target corpus  $\mathbf{t}$ . We will define the indicator function  $\mathbb{1}_{\mathbf{t}}$  by:

$$\mathbb{1}_{\mathbf{t}}(c) = \begin{cases} 1, & \text{if } t = c \\ 0, & \text{otherwise} \end{cases}$$
(2)

We will sample n corpora  $c_1, ..., c_n$  from the hierarchical bag of words model. We will estimate the marginal likelihood of the target corpus  $\mathbf{t}$  by the following formula:

$$\sum_{\theta \in \Theta} \Pr(\mathbf{C} = \mathbf{t}, \Theta = \theta) \approx \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}_{\mathbf{t}}(c_i)$$
(3)

Define a procedure estimate-corpus-marginal, which takes five arguments: corpus, sample-size, sent-len, corpus-len, and theta-probs. The argument corpus is the target corpus whose marginal likelihood we want to estimate. sample-size is the number of corpora that we are going to sample from the hierarchical model (its value was 1000 in the discussion above). The arguments corpus-len and sent-len characterize the number of sentences in the corpus and the number of words in each sentence, respectively. The argument theta-probs is the prior probability distribution over  $\theta$  for our hierarchical model.

The procedure should return an estimate of the marginal likelihood of the target corpus, using the formula defined in Equation 3.

Hint: Use sample-thetas-corpora to get a list of samples of theta-corpus pairs, and then use get-corpus to extract the corpus values from these pairs (and ignore the theta values).

**Problem 10:** Call (estimate-corpus-marginal my-corpus 50 2 2 theta-prior) a number of times. What do you notice? Now call (estimate-corpus-marginal my-corpus 10000 2 2 theta-prior) a number of times. How do these results compare to the previous ones? How do these results compare to the exact marginal likelihood that you computed in Problem 2?

**Problem 11:** These functions will be useful for us in the next problem.

```
(defn get-count [obs observation-list count]
  (if (empty? observation-list)
      count
      (if (= obs (first observation-list))
            (get-count obs (rest observation-list) (+ 1 count))
            (get-count obs (rest observation-list) count))))

(defn get-counts [outcomes observation-list]
  (let [count-obs (fn [obs] (get-count obs observation-list 0))]
      (map count-obs outcomes)))
```

In Problem 9, we introduced a way of approximating the marginal likelihood of a corpus by using random sampling. We can similarly approximate a conditional probability distribution by using random sampling.

Suppose that we have observed a corpus  $\mathbf{c}$ , and we want to compute the conditional probability of a particular  $\theta$ . We can approximate this conditional probability as follows. We first sample n theta-corpus pairs. We then remove all of the pairs in which the corpus does not match our observed corpus  $\mathbf{c}$ . We finally count the number of times that  $\theta$  occurs in the remaining theta-corpus pairs, and divide by the total number of remaining pairs. This process is called *rejection sampling*.

Define a function rejection-sampler which has the following form:

(rejection-sampler theta observed-corpus sample-size sent-len corpus-len theta-probs)

We want to get an estimate of the conditional probability of theta, given that we have observed the corpus observed-corpus. sample-size is a positive integer, and we will estimate this conditional probability by taking sample-size samples from the joint distribution on theta-corpus pairs. The procedure should filter out any theta-corpus pairs in which the corpus does not equal the observed corpus. In the remaining pairs, it should then count the number of times that theta occurs, and divide by the total number of remaining pairs.

Hint: Use get-counts to count the number of occurrences of theta.

**Problem 12:** Call (rejection-sampler theta1 my-corpus 100 2 2 theta-prior) a number of times. What do you notice? How large does sample-size need to be until you get a stable estimate of the conditional probability of theta1? Why does it take so many samples to get a stable estimate?