Problem Set 0: Review of probability

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This problem set is graded out of fifteen points, but like all problem sets, will count towards 6% of your final grade. It is due on T-Square at the beginning of class on August 26. It will be accepted up to 72 hours late, with a penalty of 20% per 24 hour period.

Using LaTeX to typeset your answers is encouraged, but not required. All work must be your own.

1 Zombie Bob?

Alice knocks on Bob's door, and hears the reply *graagh!*. There are two possibilities:

- 1. It is Bob. Alice estimates that Bob's likelihood of saying graagh is 10^{-5} .
- 2. It is Zombie Bob. Having seen many zombie movies, Alice estimates that Zombie Bob's likelihood of saying *graagh* is 1.

1.1 Bayes rule (1 pt)

Alice is a cold-eyed realist, and her **prior** probability that Bob could become a zombie was one in a million. After hearing Bob's reply *graagh!*, what is Alice's posterior belief about whether Bob is a zombie? Give an answer that is correct to at least three decimal points.

1.2 Expected utility (1 pt)

Having heard Bob say *graagh*, Alice can stay or run away. She has the following *utility* function:

- u(stay, Bob) = 0. Alice gets to talk to Bob.
- u(stay, Zombie Bob) = -10. Zombie Bob eats Alice's brain.
- u(run, Bob) = -1. Alice runs, and is embarrassed.
- u(run, Zombie Bob) = 1. Alice runs, and sells her story to AMC.

What is Alice's expected utility under each strategy?

1.3 The chain rule and marginal probabilities (1 pt)

Alice has been studying karate, and has a 50% chance of surviving an encounter with Zombie Bob. If she opens the door, what is the chance that she will live, conditioned on Bob saying *graagh*? Assume there is a 100% chance that Alice lives if Bob is not a zombie.

2 Necromantic Scrolls

The Necromantic Scroll Aficionados (NSA) would like to know the author of a recently discovered ancient scroll. They have narrowed down the possibilities to two candidate wizards: Anna and Barry. From painstaking corpus analysis of texts known to be written by each of these wizards, they have collected frequency statistics for the words *abracadabra* and *gesundheit*, shown in Table 1

	abracadabra	gesundheit
Anna	5 per 1000 words	6 per 1000 words
Barry	10 per 1000 words	1 per 1000 words

Table 1: Word frequencies for wizards Anna and Barry

2.1 Bayes rule (1 pt)

Catherine has a prior belief that Anna is 80% likely to be the author of the scroll. She peeks at a random word of the scroll, and sees that it is the word *abracadabra*. Use Bayes' rule to compute Catherine's posterior belief that Anna is the author of the scroll.

2.2 Multiple words (2 pts)

Dante has no prior belief about the authorship of the scrolls, and reads the entire first page. It contains 100 words, with two counts of the word *abracadabra* and one count of the word *gesundheit*.

- 1. What is his posterior belief about the probability that Anna is author of the scroll? (1 pt)
- 2. Does Dante need to consider the 97 words that were not *abracadabra* or *gesundheit*? Why or why not? (1 pt)

2.3 Extra credit (2 pts)

The word frequencies in Table 1 are based on statistics from a corpus of 10,000 word tokens per wizard. Consequently, they are only *estimates*, and the certainty of these estimates is limited by the variance of the estimator. A better approach might be to marginalize over the frequency parameters (written θ), and compute the probabilities of authorship by conditioning directly on the corpus counts (written z). But since the frequency parameters are continuous, marginalization involves solving an integral:

$$P(x|z,y) = \int P(x,\theta_y|z_y)d\theta_y = \int P(x|\theta_y)P(\theta_y|z_y)d\theta_y, \tag{1}$$

for each value of $y \in \{\text{Anna, Barry}\}$. As it turns out, this is not as difficult as it might seem, with a clever selection of the prior density function $P(\theta_y|z_y)$. Select the appropriate density function so that this integral can be solved, and use it to recompute Catherine's belief about the authorship of the scroll from seeing the word *abracadabra*.

3 Sentence lengths

Consider the following *model* for writing sentences:

- While not done:
 - With probability (1λ) , stop and break out of the loop.
 - With probability λ , write a word and continue looping.

This model produces sentences of stochastically varying lengths.

3.1 Maximum likelihood estimation (2 pts)

Given a corpus of sentences, with lengths $\{\ell_1, \ell_2, \dots, \ell_N\}$, compute the maximum-likelihood estimate of λ . This means that you want to find the value of λ that maximizes the likelihood function, $P(\ell_{1:N}|\lambda) = \prod_n P(\ell_n|\lambda)$.

It is equivalent (and easier) to maximize the log likelihood, $\sum_n \log P(\ell_n|\lambda)$, so you should do this. Specifically, take the derivative with respect to λ , and solve. Write your answer in terms of the average sentence length $\bar{\ell} = \frac{1}{N} \sum_i^N \ell_i$.

3.2 Expectations

1. What is the expected sentence length, given a parameter λ ? Since sentence lengths are discrete, the expectation is a weighted sum,

$$E[\ell] = \sum_{\ell=0}^{\infty} \ell P(\ell)$$
 (2)

Here is a cheatsheet with some identities: https://www.tug.org/texshowcase/cheat.pdf. I believe you will find one of them (on the first page) to be useful. (2 pts)

- 2. What is the modal (most probable) sentence length? (1 pt)
- 3. **Extra credit**: When the modal value is different from the expected value, the probability distribution is said to be *skewed*. Propose a probability distribution for which the expected sentence length would be no more than one word more or less than the modal sentence length. (1 pt)

4 Part-of-speech tagging accuracy

Part-of-speech tagging is a key component of the NLP pipeline, in which each word token is assigned an element from a set of syntactic tags, such as noun, verb, adjective, etc. Felicia has built a part of speech tagger with 95% per-word accuracy — it gives the right tag 95% of the time.

- 1. Suppose a sentence contains n words, and that the chance of making an error on each word is independent and identically distributed (IID). What is the chance of tagging the entire sentence correctly? Give the approximate answer for n = 10. (1 pt)
- 2. Suppose the tagger has a particularly difficult time with verbs almost all its errors are made on verbs. Will the percentage of sentences with errors be higher or lower than under the model in which errors are IID? Why? (1 pt)
- 3. Suppose that when the tagger makes an error, it goes "off the rails," and is very likely to immediately make another error (and then another, and so on). Will the percentage of sentences with errors be higher or lower than under the independent-error model? Why? (1 pt)