ANLP Assignment 1 2023 Solution Notes and Marking Information

This document provides some notes on the solutions to Assignment 1, along with information about how we are marking it, based on submissions that we've looked at so far.

General Points

Some students lost marks due to difficulty with terminology. To set things straight:

- Some students referred to smoothed estimates as MLE also. However, this is incorrect: once you are using smoothing, it is no longer MLE. You could get away with saying something like "we used smoothed MLE estimates" because at least that is clear you are not actually using straight MLE. But it's better to simply say "we used smoothed estimates", "we used add-alpha smoothing to estimate probabilities", or something similar.
- All of these (MLE, add-alpha, etc.) are different estimation methods. In particular, smooth- ing methods result in Maximum-A-Posteriori (MAP) estimation, as they can be interpreted as a prior over "parameters" (normalised n-gram counts, in this case).

Task 1

Most people got full or nearly full marks on this question. We were looking for some recognition that you had considered what to do about newline characters (i.e., end of sentence, since the training data had one sentence per line). You could either insert special sentence boundary markers (as in our toy example and model-br.en), or replace the newline with a space which at least provides a special context (period followed by space) for choosing what character to begin the next sentence with. You should also explain why: if you don't, then when generating from the model (later question), there's no proper history to condition on for the first two characters. (Additional pros/cons might be mentioned as well.)

Additionally, some of you deviated from the instructions on pre-processing the text by substi tuting characters (instead of removing them), e.g. mapping all punctuation marks into periods, or removing diacritics such as umlauts. A tiny amount of points were deducted in this case, as instructions were very specific and you had Task 6 to explore alternative variants.

Task 2

To get nearly full marks on this question, your answer needs to identify add-alpha smoothing as the most likely, with good justification, likely including some specific examples of trigrams you looked at. In particular:

• MLE is ruled out (i.e., some form of smoothing is used) because there are no zero probabilities.

- Backoff/interpolation are very unlikely because so many unlikely trigrams have the same probability, regardless of their final bigram. For example, the trigrams c., cv, and cy (where represents a space) all have the same probability. This could happen under add- alpha or Good-Turing if all three are unseen in the training data (which is plausible). But using backoff or interpolation, the probabilities would be estimated by combining the trigram information with bigram information: specifically, the estimated bigram probabilities P (.|c), P (v|c), and P (y|c). But notice that, unlike the trigrams, these are not likely to all have zero counts, because it's perfectly reasonable to have a c before a full stop, or a cy in a word (probably at the end of the word), whereas cv even as a bigram is very bad. So using backoff or interpolation, we'd probably end up estimating P (|c.) and P (|cy) as higher than P (|vc).
- This leaves add-one (Laplace), add-alpha, Good-Turing (and Kneser-Ney) as possibilities. (Some people made the jump from saying add-alpha is possible, to concluding that add- alpha is the right answer. Please be careful with your reasoning: simply showing that all your evidence fits one hypothesis is not the same as showing that other hypotheses are ruled
    - ut.)
- If your reasoning was clear and got as far as that, you will have got most of the marks. But you can go further. For example, there are a large number of trigrams that all have the

- same probability of 3.333e-02 = 1/30, and these look like unlikely trigrams with unlikely histories (for example, all the trigrams that begin with a space followed by a full stop). One can speculate that probably all of these trigrams, as well as their bigram history, have counts of 0. Under those circumstances, add-alpha smoothing would indeed yield a probability of 1/30. But Good- Turing (unless combined with backoff or interpolation) would actually be undefined, because it
- nly adjusts the trigram counts (numerator) but doesn't change the bigram counts (denominator)!
    - Although this was not expected, you can actually go even further and determine the value of
- alpha used in this language model (if you assume reasonably that add-alpha smoothing was used, based on the above). We invite you to have a think about how you could analyse the model-br.en file to deduce this value. Hint: think about which sort of trigram probabilities would be helpful in determining α. Task 3 Most people should expect to get between 21-31 marks on this question. We divided the marking into two types of criteria: "core aspects" and "additional aspects". An answer that is very strong
- n the core aspects would have the following characteristics:
    - Clear explanation with correct use of terminology (see General Points at the top) and ap- propriate scientific style (e.g., no "history-telling"—see the assignment handout if you're not sure what I mean).

- Must use some form of smoothing, and give a full justification. (i.e., just saying "we used smoothing to avoid zeros") is only part of the justification: why do you need to avoid zeros,
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especially in the context of this assignment? You need to say something about making predictions or computing perplexity on a test document.

- Acknowledgement of the weaknesses of the chosen method, and mention some alternatives. Even better if you point out that using add-alpha is actually not as bad with characters as it is with words, because the "vocabulary" size is small.
- Define all terms in equations, and say what they refer to in this context (that is, they refer to character trigrams/bigrams, and V is the number of distinct characters, i.e. 30).
- Probabilities for ng should be non-zero for all 30 possible continuations.
- Comments on both some of the high-frequency continuations (like ng)—ideally giving ex- amples of real English words with these combinations—and some of the low-frequency ones. Most answers do not satisfy all these points. Those that cover most of them will be closer to

- the high end of the range on "core aspects" (27-28 marks). Marks of less than 21 overall usually mean an incomplete implementation, severe problems with the explanation, or failure to use any smoothing at all, possibly along with problems in clarity.
  - In addition to the core aspects above, we are awarding additional marks in some cases for
- answers that went a bit further with the smoothing method and/or hyperparameter optimisation, but only if these were actually justified and explained clearly and appear to be implemented correctly. In other words, trying something more complex is not worth as much as doing well on the core aspects, and must be done correctly to get credit. Some students who attempted more complex solutions got worse marks overall than other students who did a very good job on the basics. Task 4 Most people had the right general idea of what to do here but some didn't implement it quite right. For those who did not, I provide below an example of the kind of output we were looking for. To create it, we first learned the trigram character model from the training corpus (or read it in from model-br.en), and then generated each character in turn by sampling from the conditional probability distribution defined by the previous two characters. The key parts to getting this correct are understanding that:
  - You need to sample from the conditional distribution, not a joint distribution. For example, if the last two generated characters are th, then you should sample the next character c according to P (c|t, h) and not from P (t, h, c).
  - Because the history changes at each point, so does the distribution you are sampling from. For example, if you randomly chose i as the next character after th, then the next character after that would be sampled from P (c|h, i).
  - When choosing the next character, it must be chosen randomly according to the full condi- tional distribution. It is not correct to choose the next character according to the maximum
    - f the distribution, or a subset of the full distribution.
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• When starting to generate, you need to begin with markers indicating the beginning of the sequence. And when the model generates an end of sequence, you just need to begin again in the same way (rather than, for example, doing something to avoid generating the end of sequence).

A good textual description should demonstrate that you understand those concepts, typically by mentioning the following:

• something about how begin/end of sequence are handled. • that the 2-char history is used to determine the distribution to sample from. • that you generate by sampling from the distribution, not taking the most probable option. If you used pseudocode to describe what you did, it should indicate the same points, and crucially needs to be easily understandable. Typically, that means a mixture of symbols and text; pseudocode that consists entirely of symbols/variables, especially if they are not very clearly explained, is rarely easy to understand. Pseudocode that looks basically like real code also often defeats the purpose of being easier to understand than real code. The reason for asking you to generate 300 characters was so you'd have enough to see some of the differences. A few people stopped after generating a single sequence, which isn't enough to do this. Generating everything as a single sequence (replacing the end-of-sequence markers with nothing, instead of leaving in or replacing with a newline) is also not ideal, since technically these are separate sequences and looking at the difference in sequence length is important. Example output: First, here are some samples from the English trained model using different values of alpha smoothing. Notice that the larger values of alpha do give somewhat more rubbishy sequences because they are over-smoothed, so there are quite a few sequences that never occur in training (e.g., full stops in the middle of sentences). To emphasize that, I left the begin/end of sentence marks in so it's obvious where each "sentence" is. Sample output from English training data (using add-1 smoothing): ##thie0ibil theri# ##uwhisionethe ber eurepelobidteurat hat wilit inat ing eur the mosjpgvdvout imrs come do moswturaffolat of sidelos.# ##ing the ch ince tegive thanotend iwqmtnjill ther wis is mograiling the i diregiveles.# ##i do plqterglyjzons maiqm# ##we to thinlyps.# ##fichineressionvated forchariatit thantly i .eced.# ##to beithavelo00# ##thisheral and pors ther by is sen a in thropme ta.o my it housfecievat pend oufsh re droessin poreprourrecautgf.i it stake rei# ##the berest the sxmg# ##lv# ##the statiount mit ission Sample output from English training data (using add-0.1 smoothing):

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Sample output from English training data (using add-0.01 smoothing):

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Now, here's some sample output from model-br.en:

##th your a scrabyes.# ##cant there dow cou.# ##is one.# ##now ame spook to.# ##you kno.# ##that do you go.# ##he yone ant.# ##your.# ##a likes is twou fand ged one cand do.# ##here a like hi.# ##is for liff.# ##whats thely.# ##what callo.# ##thi kit you whatchy hos the a le come youseed say.# ##wand howere.# ##se mou we bigby.# ##thaid towele.# ##a seep.# ##kin dooke thats rie one put.# ##its say therose like and book does top.# ##what ase for sed he this.# ##brus.# ##whattle thats ards a areephow wits lent ats in put down.#

##it me on.# ##right smay do gray.# ##te book

To get most of the marks in this question, your generated sequences should look roughly like these, you should have a clear and concise explanation of what you did to generate them, and you should have mentioned a few of the following points:

- model-br produces shorter words and shorter sentences than your trained model.
- Its words also look simpler, with more common character sequences.
- You should propose a possible explanation, which could be that we used a better smoothing method, but seems more likely to be due to a different training corpus that has different properties. To get full marks, we would like to see a bit more thought/analysis. Ideally you might have

- tried generating more sequences from model-br, and if you did you might start to notice that it generates a lot of sequences like 'dog', 'doggie', 'daddy', 'hello', 'what', 'book', etc. This fact, together with the other properties noted above, suggests that the training corpus was nothing like the Europarl data. In fact we used a transcript of child-directed speech (much like the data from Lab 1, but cleaned up a bit). Task 5 To do well here, you need to:
  - Get the right perplexity values
  - Say that you can guess the language of the test doc according to the training language which produced lowest perplexity value
  - Include some reasonable discussion about the perpexity of a new document (see below).
- Some notes on common issues:
  - Some submissions have the perplexity values wrong. The right values will depend on exactly which estimation method you used, but in general the value for English will be around 8-10 and values for Spanish and German will be above 20. In other words, there is an obvious difference between the right language (English) and the other ones. Many people tested their perplexity function on the simple example from Q0. This is a good start, but may not be sufficient. Whenever you write code, it's a good idea to consider what range of values you expect to get in the results. In this case, you might reason as follows:
    - – There are 30 different characters. A uniform distribution over these would have entropy
      - (average negative log prob) of log2 30, or about 5. Perplexity is based on cross-entropy:
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the average negative log prob of some data under my model. A perplexity of 30 (cross entropy of about 5) would mean that my model is about as good at predicting the sequence it sees as a random uniform model would be at predicting a sequence of random characters uniformly distributed among 30 possible characters. In other words, my model's predictions on this data are about as good as the best model's predictions could be on a completely unpredictable sequence over the same number of characters.

– This line of reasoning should lead you immediately to to the conclusion that any rea sonable model should have a perplexity (considerably) lower than 30 on data that looks similar to what it was trained on (since the data is not actually uniform random).

– On the other hand, if the model is presented with data that are very dissimilar to what it was trained on, then its predictions could actually be as bad or worse than a random model's predictions on random data. So it wouldn't be totally surprising to get perplexities close to 30 for dissimilar data. – Also, suppose (as many students did) you end up with perplexities that are extremely similar for the three test models: say, 9.1, 9.2, and 9.3. These are saying that your three models' predictions are as good as a uniform random model on uniform random sequences containing (respectively) 9.1, 9.2, or 9.3 distinct characters. But the difference between 9.1 and 9.2 distinct characters is not much at all. So it should seem implausible that your models, which are trained on completely different languages, have only that much difference in perplexity. This should give you a hint that either you're computing perplexity wrong, or you estimated your models incorrectly, or both. – Finally, perplexity cannot be less than 1, because entropy cannot be less than 0. And if you're even getting values just a bit bigger than 1, you should be probably be suspicious that they're too low, and again go looking for a bug (or convince yourself somehow that you are actually correct).

• Most people realized that zero probabilities present a problem for computing perplexity. However, it is not correct to simply skip over them. Doing so is not only incorrect according to the definition of perplexity, but also presents practical problems. Consider that for a test document in a language that doesn't match the training document, there are likely to be many more unseen trigrams than there are in a test document from a matching language. If you simply skip over them, you are losing a huge amount of information regarding the fact that your test document doesn't look like your training document. You could actually end up concluding that the non-matching test document has better perplexity than the matching document, simply because you are ignoring so much of the non-matching information. The zeros are telling you something: your model predicts that something never happens, but actually it does. So you get infinite perplexity because your model is infinitely wrong. The problem is simply that you can't make sensible comparisons between different things that are all infinitely wrong. • Most people stated that perplexity could not be used to determine the language of a new test document because perplexity is only a relative measure. This is correct if all you know is the perplexity of the new test document (let's call it d1 under your English LM. However, if

you have already run your program on the test document provided with the assignment (d0) after training on the German and Spanish data, you would also know the perplexity of that d0 under the German and Spanish language models. As noted above, there is a pretty big difference in perplexity between the three models on d0. Given that information, it might be possible to tell fairly accurately whether d1 is also in English or not: is its perplexity under the English LM close to that of d0, or is it closer to the perplexity of d0 under the German or Spanish models, which we might take as typical "cross-linguistic" perplexity values?

An even better answer might suggest (or even try) ways to estimate how much variability in perplexity might occur for different English test documents. You might, for example, try some new documents yourself, or you might compute the perpelxity of the given document under model-br.en. If you did, you'll notice it's a lot higher than under the model from the English training data! For that reason, using the very basic smoothing methods here, it probably isn't possible to correctly identify the language of a test document. But if we were using a better model/estimation method (e.g., higher order n-grams with better smoothing), and we knew the genre of text, we almost certainly would be able to.1

Answers that just mention the first sentence above ("entropy is relative") get some credit, mainly because the question is ambiguous about what information is available. But for many answers it would be nice to see bit more consideration.

Task 6

Many pairs did not attempt this question. But for those who did: simply implementing a more complex method is not sufficient for many (if any) marks by itself: as noted in the assignment, you must address a specific question. It's even better if you propose a hypothesis about what you expect to find. I would expect to see things like exploring the effect of different orders of n-grams, more complex smoothing methods, optimising α (if you didn't already do that in Q3), and looking at other data sets. I particularly appreciated answers extending the analysis to other domains or languages. Marks are based on the difficulty and/or creativity of the task, a clear and correct description of the method with evidence of correct implementation, and clearly presented results and discussion.

1Language identification for multi-genre text is much harder, but does use some of the ideas we've explored here and in the rest of this course. For example, see langid.py: An Off-the-shelf Language Identification Tool (Liu and Baldwin, 2012): www.aclweb.org/anthology/P12-3005