# Exercises on $\boldsymbol{n}$-gram language models, spelling correction, text normalization 

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#### Abstract

Submit as a group (of 3-4 members) a report for exercise 4 (max. 5 pages, PDF format). Explain briefly in the report the algorithms that you used, how they were trained, tuned etc. Present in the report your experimental results and demos (e.g., screenshots) showing how your code works. Do not include code in the report, but include a link to a shared folder or repository (e.g. in Dropbox, GitHub, Bitbucket) containing your code.


1. (i) Using Laplace smoothing (or better) and (possibly a subset of) an English corpus (e.g., the English part of Europarl, available from http://www.statmt.org/europarl/), estimate the probabilities of all the word bigrams of the five candidate word sequences $t_{1}^{4}$ of slide 27. (ii) Using a bigram language model and the bigram estimates of the previous question, estimate the probability of each one of the five candidate sequences $t_{1}^{4}$ of slide 27. (In practice, $n$-gram language models compute the sum of the logarithms of the $n$-gram probabilities of each sequence, instead of their product. Why?) (iii) Using as $P\left(w_{i} \mid t_{i}\right)$ the inverse of the Levenshtein distance (e.g., as computed by http://www.let.rug.nl/~kleiweg/lev/) between $w_{i}, t_{i}$ (or better probability estimates, which satisfy $\sum_{w_{i}} P\left(w_{i} \mid t_{i}\right)=1$ ) and the formulae of slide 30, estimate $P\left(t_{1}^{4} \mid w_{1}^{4}\right)$ for each one of the five candidate sequences $t_{1}^{4}$ of slide 27 .
2. [Optional material for the TEA course.] (i) Check the Levenshtein distance calculations of the table on slide 23. (ii) Implement (in any programing language) the dynamic programing algorithm that computes the Levenshtein distance (slides 18-23); your implementation should print tables like the one of slide 23 (without the arrows). (iii) Optionally extend your implementation to accept as input a word $w$, a vocabulary $V$ (e.g., words that occur at least 10 times in a corpus), and a maximum distance $d$, and return the words of $V$ whose Levenshtein distance to $w$ is up to $d$.
3. Compute the entropy in the cases of slide 37 (e-mail messages). Hint: for $P(C) \rightarrow 0$, use L'Hôpital's rule.
4. (i) Implement (in any programming language) a bigram and a trigram language model for word sequences, using Laplace (slide 8) or (much better in practice) Kneser-Ney smoothing (slide 13). Train your models on a training subset of a corpus (e.g., from the English or Greek part of Europarl). Include in the vocabulary only words that occur, e.g., at least 10 times in the training subset; use the same vocabulary in the bigram and trigram models. Replace all out-of-vocabular (OOV) words (in the training, development, test subsets) by a special token *UNK*. Assume that each sentence starts with the pseudo-token *start* (or the pseudotokens *start $1^{*},{ }^{*}$ start $2 *$ for the trigram model) and ends with $*$ end $*$.
(ii) Check the log-probabilities that your trained models return when given (correct) sentences from the test subset vs. (incorrect) sentences of the same length (in words) consisting of randomly selected vocabulary words.
(iii) Demonstrate how your models could predict the next (vocabulary) word, as in a predictive keyboard (slide 33, center).
(iv) Estimate the language cross-entropy and perplexity of your models on the test subset of the corpus, treating the entire test subset as a single sequence, with *start* (or *startl *, *start $2 *$ ) at the beginning of each sentence, and *end* at the end of each sentence. Do not
include probabilities of the form $P\left({ }^{*} \operatorname{start} * \mid \ldots\right), P\left({ }^{*} \operatorname{start} 1 * \mid \ldots\right)$ or $P\left({ }^{*} \operatorname{start} 2 * \mid \ldots\right)$ in the computation of perplexity, but include probabilities of the form $P\left({ }^{*}\right.$ end $\left.{ }^{*} \mid \ldots\right)$.
(v) Optionally combine your two models using linear interpolation (slide 15) and check if the combined model performs better.

You are allowed to use NLTK (http://www.nltk.org/) or other tools for sentence splitting, tokenization, and counting $n$-grams, but otherwise you should write your own code.

