ELEC-E5510 — Exercise 4: Continuous speech recognition

The goal of the exercise is to get familiar with continuous speech recognition using HTK and SRILM tools.

Use the submission instructions for returning your answers. **Deadline is Wednesday 22.11.2023 at 23:59**.

When doing these exercises from home use a Maari-B computer.

Preparations

The data used in the exercise is located in the directory shown below. Let's set a shortcut variable and the path. If your shell is `/bin/zsh` or `/bin/bash`, write:

```
data=/work/courses/T/S/89/5150/general/ex4
PATH="$PATH:/work/courses/T/S/89/5150/general/bin"
```

If your shell is `/bin/tcsh`, write:

```
set data = /work/courses/T/S/89/5150/general/ex4
set path = ($path /work/courses/T/S/89/5150/general/bin)
```

HTK-models used in this exercise are under `$data`, with the usual names `config`, `macros` and `hmmdefs`. The models have been trained from the famous Wall Street Journal corpus (WSJ0), which contains about 15 hours of speech from 80 speakers. The models are rather complex context-dependent triphone models with tied mixture states. Because of their size, they are stored in binary format, so unlike earlier, you can not view the model files with a text editor.

In all of the questions, you are requested to report the commands that you used to get the results.

Note that the evaluation sets used in this exercise are rather small, so that the recognition time remains reasonable. In reality, larger test sets would be preferable, so that more reliable error measurements could be obtained.

Grammar based recognition network

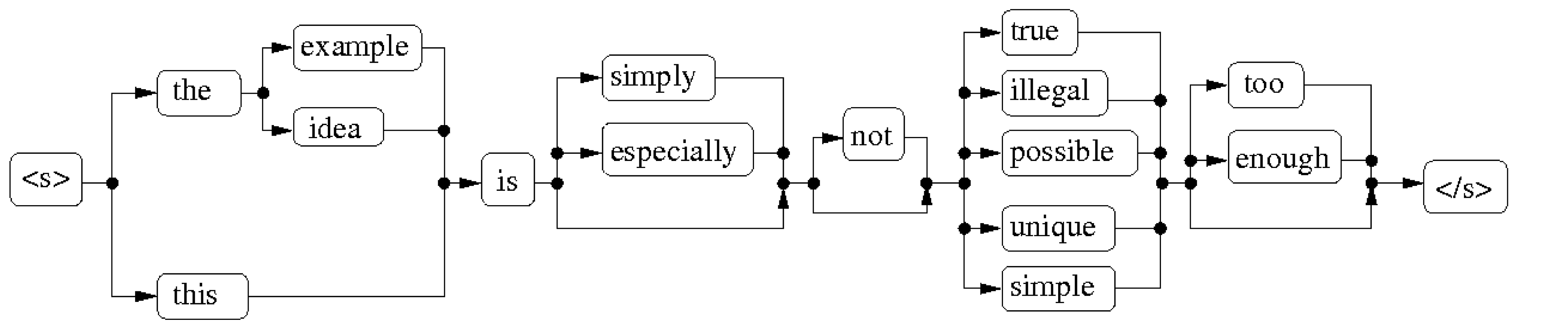
Continuous speech recognition always requires some language information to restrict the recognition. Simple dictionary based recognition is rarely enough for achieving acceptable recognition accuracy. One of the simplest forms of additional language restriction is a *task grammar*. It defines the allowed word sequences or sentences as word networks or finite state machines. For simple tasks this can be a very effective, but for more complex cases defining the search network this way can be troublesome.

HTK supports grammar based recognition networks via `HParse` tool. Take a look at an example in HTK book (available under `/work/courses/T/S/89/5150/general/doc`) on page 25, page 184, or the reference pages 297-300, on how to define a grammar with HTK.

Question 1

a)

The picture below defines an artificial grammar for simple statement sentences. Define a corresponding grammar in HTK format and convert it to a recognition network using `HParse`.



In the grammar definition you need to escape the sentence start symbol as \<s\> and the sentence end symbol as \<\/s\>. The tool is also case sensitive. Once converted, you can test that the grammar gives only allowable sentences by looking at the output of `HSGen`:

```
HSGen grammar_net.htk $data/grammar.vocab
```

where grammar_net.htk is the network compiled with `HParse`.

Using the recognition network and the above mentioned models, recognize a small test set `$data/grammar.scp`. Use `HVite` for decoding, such as:

```
HVite -T 1 -i grammar.rec -H $data/macros -H $data/hmmdefs \
  -C $data/config -w grammar_net.htk -s 10.0 -t 200.0 \
  -S $data/grammar.scp $data/grammar.dict $data/tiedlist
```

Include in the report the **grammar definition you constructed, the commands you used, and the individual recognition results as reported by `HResults`:**

```
HResults -h -t -I $data/grammar.mlf /dev/null grammar.rec
```

Why did the recognizer make mistakes?

b)

Let's try the same recognition task with an n-gram language model. File `$data/grammar.sent` includes training sentences generated from the grammar. These were generated using HTK tool `HSGen`. Using SRI tool `ngram-count` as instructed in Exercise 3, train two 2-gram models, **with and without smoothing** (for the smoothed model, use options `-interpolate -cdiscount1 0 -cdiscount2 0.5`).

You need to modify the unsmoothed language model in a text editor (it is text-based ARPA format), because ngram-count compensates round-off errors with non-infinite back-off weights: Under \1-grams: section, replace all back-off weights (the third column) with -99, which represents minus infinite. This makes sure the language model can not generate unseen word sequences.

Build a recognition network out of the language models with `HBuild`. For example,

```
HBuild -s "<s>" "</s>" -n grammar_2gram.lm $data/grammar.vocab grammar_2gram_net.htk
```

creates a recognition network from 2-gram model `grammar_2gram.lm`. Run the recognition and see the results with `HResults` as in part a). **Include the commands and the output of `HResults` to the report. How did the recognition results change** with these language models? Explain **why.**

A note about HResults output

Now that we are evaluating continuous speech recognition, we can take a closer look at the error measures reported by `HResults`. The tool divides the errors to three categories: substitutions, deletions, and insertions. These refer to the word level editing operations needed to match the transcription to the recognition hypothesis. Usually only the summed Word Error Rate (WER) is used for evaluation (shown under Err column), but this division can give a hint what kind of mistakes the recognizer is doing.

Recognizing continuous speech with HVite

Let's review the `HVite` recognition command in the previous question. Below are explanations of each of the parameters:

-T 1	Print some progress info during recognition
-i grammar.rec	The file to store the recognition output to
-H $data/macros -H $data/hmmdefs	The HMM models
-C $data/config	The general configuration file
-w grammar_net.htk	The recognition network
-s 10.0	Language model weight
-t 200.0	Beam pruning threshold
-S grammar.scp	A list of files to be recognized
$data/grammar.dict	The pronunciation dictionary
$data/tiedlist	List of triphone models

Two important parameters worth discussing are the language model weight `-s` and the beam pruning threshold `-t`. The first one defines the multiplier for the logarithimic likelihoods of the language model, applied before summing them to the loglikelihoods of the acoustic model to form the total score for each hypothesis. In case of a grammar it does not have any effect as grammars (usually) only define allowed sentences, not their probabilities. That is, all the allowed sentences are considered equally possible. N-gram models, on the other hand, operate with probabilities. Remember that smoothed N-gram models make all the word sequences of a given dictionary possible, although some might be highly unlikely. To define the influence of the language model and to adjust the "separation" between common and rare sentences, language model weight is used. The larger the value, the more the recognition favors common sentences defined by the language model. With a small weight, language model has smaller effect and the recognizer makes the decisions more according to the acoustic models.

Recognizing, or *decoding*, continuous speech is computationally hard, and several tricks are used to make it fast enough. A very common parameter in speech recognizers is the beam pruning threshold, which defines the maximum logarithmic likelihood difference between the best and alternative hypotheses at any given time. In theory different hypotheses can be fairly compared only after the acoustic and language model likelihoods have been computed for the whole utterance. In practice this is not computationally feasible, so the lower probability hypotheses are pruned away already earlier in the decoding process. Reducing the beam pruning threshold makes the recognition faster, but can lower the accuracy if the recognizer abandons lower probability hypotheses too aggressively. With a properly tuned beam threshold, this pruning does not have significant effect to the accuracy. The threshold, however, is heavily dependent on the task, the language model, and the language model weight used.

Recognizing continuous speech with HDecode

The `HVite` tool used in the previous question is a rather simple one. Its main limitation is that it can not be used with larger language models, only n-gram models up to 2-grams can be converted into recognition networks with `HBuild`. A more refined tool for large vocabulary continuous speech recognition is HTK's `HDecode`. It is restricted to triphone acoustic models, but it can natively use n-grams up to 3-grams. It is also faster then `HVite`. Using `HDecode` is similar to `HVite`, except that instead of a recognition network, a language model is provided directly. Some configurations also differ, hence an extra configuration file is used in this exercise.

File `$data/wsj_5k_eval.scp` contains the evaluation set used in the rest of the exercise. Suitable language models are provided in files `$data/wsj_5k.?gram.lm.gz`. Corresponding dictionary file for `HDecode` is `$data/wsj_5k.hdecode.dict`. Transcript file for the evaluation set is in `$data/wsj_5k_eval.mlf`. Using these files, recognizing the evaluation set with `HDecode` and the 3-gram model is done as follows:

```
HDecode -T 1 -C $data/config -C $data/config.hdecode -S $data/wsj_5k_eval.scp \
  -i results.mlf -H $data/macros -H $data/hmmdefs -t 150.0 -s 10.0 \
  -w $data/wsj_5k.3gram.lm $data/wsj_5k.hdecode.dict $data/tiedlist
```

Question 2

a)

Using the 3-gram language model, recognize the WSJ evaluation set with language model weights 12.0, 14.0, 16.0 and 18.0. Use beam pruning threshold 200.0. **Report the commands you used and the word error rate for each of the language model weight** (you can omit `-t` switch in `HResults` to have less output). **Which language model weight** gave the best recognition results?

b)

Run the recognition again with language model weights 12.0 and 18.0, but now with beam pruning threshold 220.0. **Compare the WERs to the results of the a) part. Why** does the larger language model weight require a larger beam threshold as well?

Lattice rescoring and 4-gram models

Sometimes even higher order n-grams than 3-grams are needed. HTK does not support them as such, but we can still get past the 3-gram limit. Both `HVite` and `HDecode` support writing recognition lattices instead of just the best hypothesis. These lattices are compact representations of the hypotheses considered during the recognition. The hypotheses in a lattice can be *rescored* with a higher-order language model, after which we can choose the resulting new best hypothesis as the recognition result. Another benefit is that this rescoring operation is much faster compared to full decoding. It is also possible to use lattices as a basis for acoustic rescoring with a different acoustic model.

To experiment with the lattice rescoring, let's use `HDecode` to create lattice representations of the evaluation set. Usually a 2-gram model is enough for lattice generation. Run the following:

```
mkdir lattices
```

```
HDecode -T 1 -C $data/config -C $data/config.hdecode -S $data/wsj_5k_eval.scp \
  -H $data/macros -H $data/hmmdefs -z htk -l lattices -t 175.0 -s 10.0 \
  -w $data/wsj_5k.2gram.lm $data/wsj_5k.hdecode.dict $data/tiedlist
```

Directory `lattices` now contains a separate lattice file for each of the utterance in the evaluation set. The lattices may be rather big, but it is important that they contain enough alternative hypotheses so that rescoring is able to improve the result. Beam pruning and language model weight affect the lattice generation similarly to regular decoding.

Lattices can be manipulated with SRILM tool `lattice-tool`. For example, rescoring the generated lattices with a 4-gram model is achieved with the following:

```
ls lattices/*.htk.gz > original_lattices.list
```

```
lattice-tool -order 4 -in-lattice-list original_lattices.list \
  -read-htk -lm $data/wsj_5k.4gram.lm.gz -write-htk -out-lattice-dir rescored
```

The rescored lattices are placed in the `rescored/` directory. Next we can use lattice-tool to find the best hypotheses after rescoring and compute the word error rate.

```
ls rescored/*.htk.gz > rescored_lattices.list
```

```
lattice-tool -htk-lmscale 10 -in-lattice-list rescored_lattices.list \
  -read-htk -viterbi-decode | $data/viterbi2mlf.pl > rescored/rec.mlf
```

```
HResults -h -I $data/wsj_5k_eval.mlf /dev/null rescored/rec.mlf
```

Option `-htk-lmscale` defines the language model weight.

Question 3

Do the following two tasks ***without*** *running HDecode again*. **Report the commands used and the WER results from `HResults`.**

a)

Extract the recognition results from the original lattices (**BEFORE** rescoring) and **evaluate their WER.** Use language model weight 18.

b)

Fetch the best paths from the 4-gram **rescored lattices** using language model weights 10.0, 14.0, 18.0, 22.0, 26.0 and 30.0. Report the WER results. **Which weight now gave the best result?**

Question 4

Consider different speech recognition applications. **When would you use an n-gram model trained from a large text corpus? When would you use other kinds of language models?**

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