

CS4248 Assignment 2

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1 Introduction

This assignment requires us to build a Part-of-Speech (POS) tagger, using training data from part of the Penn Treebank. The method used in our approach has to employ a Hidden Markov Model (HMM). This entails learning from the training data a set of parameters required for the HMM. Table 1 shows the various sets of data we have to collect for this particular assignment.

In the following sections, we will explain in detail how individual aspects of the HMM was created, outlining some of the technical difficulties faced. We also experiment with two simple smoothing techniques, Laplace (add-one) and Witten-Bell smoothing. The two techniques will be evaluated according to their precision, recall and F1 measures.

2 Learning from `sents.train`

The `sents.train` dataset contains 39,832 lines, each word annotated with POS tags. In order to extract the relevant information we count the transitions.

To obtain $p(s_i | s_{i-1})$, we need to count the different number of times one tag is followed

Name	Description
V	all unique words
S	all unique POS tags
$p(s_i s_{i-1})$	transition probability from one POS tag to another
$p(w s)$	probability of seeing a word given a POS tag

Table 1: Parameters for a POS tagger HMM

by another. For each line, we extract the POS for each token, leaving a list of POS tags. We then prepend a '^' at the beginning, and a '\$' character at the end. This ensures that the probabilities for a given POS starting a sentence are also taken into account.

Another preprocessing step performed was to change all instances of numeric tokens, and replacing all digits with \#. For example, '\$25.50' will be converted to '\$\#\#.\#\#'. This reduces the many different combinations of numbers down to a common token that would have a higher probability given the tag CD.

Going through the file, we maintain a dictionary of the following items:

Name	Description
$C(s_{t-1}, s_t)$	The number of times a POS tag occurs at time t after a POS tag occurs at time $t - 1$
$C(s_t, s_{t-1})$	Count of transitions in reverse.
$C(s, w)$	Count of words given a POS tag.
$C(w, s)$	Count of POS tags given a word.

With this data, we can now perform different smoothing methods. The smoothing method is modular in our implementation, so as long as the counts are present, we can calculate the smoothed probabilities.

3 Evaluation

We performed evaluation for the POS tagger using two types of smoothing methods, Laplace smoothing using $B = 1$ (or add-one smoothing) and Witten-Bell smoothing. The tagger performs smoothing for both conditional probabilities, $p(w | q)$ and $p(q_t | q_{t-1})$.

3.1 Different smoothing methods

Using the **add-one smoothing**, we run 10-fold cross validation using `sents.out`. The results are shown in Table 2.

The results show that add-one smoothing causes a bad recall rate. This means that some of the words are tagged erroneously, but generally distributed throughout the other tags, such that they do not affect the other recall measures much. This suggests that the probability distributions given after smoothing spread the density out over the words and part of speech tags too much.

Fold	Recall	Precision	$F1$
1	0.8645	0.7569	0.8618
2	0.8722	0.7702	0.8775
3	0.8726	0.7776	0.8656
4	0.8794	0.7599	0.8322
5	0.8924	0.7920	0.8626
6	0.8994	0.7603	0.8477
7	0.9110	0.7822	0.8523
8	0.8408	0.7705	0.8717
9	0.8689	0.7698	0.8462
10	0.8608	0.7811	0.8696
Average	0.8762	0.7721	0.8587

Table 2: 10-fold validation using add-one smoothing

Fold	Recall	Precision	$F1$
1	0.8541	0.8414	0.8719
2	0.8715	0.8978	0.8697
3	0.8595	0.9022	0.8723
4	0.8645	0.8719	0.8837
5	0.8890	0.8899	0.9024
6	0.8890	0.8766	0.8802
7	0.8924	0.8944	0.8877
8	0.8479	0.8773	0.8520
9	0.8468	0.8780	0.8736
10	0.8677	0.8929	0.8769
Average	0.8682	0.8822	0.8770

Table 3: 10-fold validation using Witten-Bell smoothing

Using **Witten-Bell smoothing**, there are fewer occurrences of such problems. This means, compared to add-one smoothing, Witten-Bell smoothing gives a better estimate of unseen instances of words given tags and tags given tags, resulting in a better overall prediction. The results are shown in Table 3.

3.2 Evaluating using `sents.devt`

With these results, we selected the Witten-Bell smoothing technique, and trained the tagger using all instances in `sents.train`, and tested it using the `sents.devt` file. This gave us a recall, precision and $F1$ measure of 0.8878, 0.9333 and 0.9015 respectively.

So, how can we improve upon this? Looking at the breakdown given the parts of speech and the confusion matrix, we can know where our tagger breaks down, and

suggest improvements to our preprocessing and smoothing steps. The following are some of the parts of speech tags that perform poorly:

NNPS (Proper Noun, plural) A considerable amount of the mistakes made for NNPS were due to mis-classifications of these tokens as NNS and NNP. One possible remedy for this is to be able to give a word that starts with a capital letter and ending with an 's' a higher probability of being an NNPS. This could be done as a special case within the smoothing step given an unseen word. Another option would be to use finite state transducers to break-down the morphology of the word.

RBR (Adverb, comparative) Some words which should be tagged as RBR are tagged as JJR. This makes sense due to the large number of overlap in the type of words used. Looking at the tags that appear before and after the occurrences of RBR, they also seem to be rather similar. One possibility to fix this would be to have higher order Markov chains for the HMM, as the distinction between JJR and RBR may be more evident further before (or after) the current token.

LS (List item marker) These are hard to distinguish from usual mentions of numbers. This is especially since one of our preprocessing steps was to make all instances of digits the same. One possible way of dealing with this would be not to modify the first tokens of a sentence, since the LS tokens appear at the start pretty often.

4 Conclusion

Despite the use of smoothing, some other optimisations could still be made to further improve the performance of our tagger. These include using a Markov Chain with order greater than 1, accounting for plurality using transducers, and taking into account the position of the word in the sentence. These, however, fall outside the scope of the assignment.

We have, however, obtained results that suggest using Witten-Bell smoothing for POS tagging works reasonably well compared to Add-one smoothing. We are also confident that our POS tagger works well in most cases.

The code for this assignment can be found at <https://github.com/shawntan/pos-tagger>.