CS-626 Assignment 2

Chunking

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1 Maximum Entropy Markov Model

1.1 Results

1Iteration	1Log Likelihood	1Accuracy
1	-1.09861	0.132
2	-0.57883	0.851
3	-0.41365	0.928
4	-0.32340	0.939
5	-0.26891	0.943

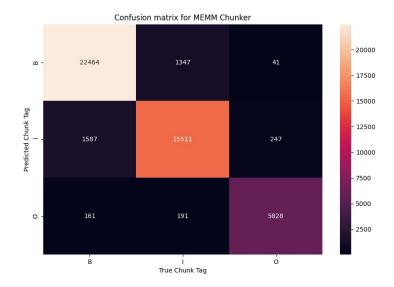
Table 1: Training values

1	1Precision	1Recall	1F1score
В	0.93	0.94	0.93
I	0.91	0.89	0.90
O	0.95	0.94	0.95
Overall	0.92	0.92	0.92

Table 2: Tag wise metrics

1.2 Error Analysis

• Very poor performance with punctuation marks like " " " ,! ? This is because these were found likely to be tagged as 'O' from the corpus, like – $P(O\mid?)=1$, $P(O\mid!)=1$, $P(O\mid;)=0.99$, $P(O\mid")=0.853$ but in some test sentences these were actually I but classifier tagged them O which results in next word to be wrongly tagged as B , since $P(B\mid O)=0.858$



• Ambiguity in comma,:

From the training corpus , comma is mostly tagged as O ($P(O\mid,)=0.946$). So , in test data it's almost every time classified as O , but some times true label is I .

Sentence -	Shopping	centers	in	Malaysia	,	Taiwan	,	Canada	and	Seattle
True	В	I	В	В	Ι	I	Ι	I	I	I
Predicted	В	I	В	В	Ο	В	Ο	В	Ο	В

we can see since comma is predicted as O, thats why the word after it is tagged as B, also Malaysia, Taiwan, Canada and Seattle being NNP, have high probablity to be tagged as B.

sentence-	Ву	encouraging	massive	,	routine	,	voluntary	testing
true	В	В	I	Ι	I	Ι	I	I
predicted	В	В	I	Ο	В	Ο	В	I

• In some cases may be true chunk tags are wrong like - in the sentence "in the Dirks"

sentence in the Dirks
True B O O
Predicted B B I

since the is DT and Dirks is NNP , also starts with capital letter , so it is most likely to be chunked as NP – B I , since $P(O \mid NNP) = 0.0028$.

- Ellipses in test sentences: consider 2 types of usage for word 'that'
 - 1. that person

here that is referring to a particular person, so should be chunked as NP - B I

2. - that the person (ellipsis - the is dropped)

True- O B I

Predicted- B (dropped) I

here that is used as conjuction, so misclassfied.

• Poor performance with interrogative sentences (starting with VBD):

sentences starting with 'Wh' words , are correctly classified as B , but sentences starting with 'Was' , 'Did' , 'Had' , are misclassified.

True - O O O
Predicted- B B B
example
Did Mr. Loeb
O B I true
B B I predicted

this is because , occurences of 'Was' =2 , 'Did'=3 and 'Had'=3 , very less for a model to learn , on the other hand $P(B \mid was) = 0.996$, $P(B \mid did) = 0.927$ and $P(B \mid had) = 0.944$, so capital letter was ignored and labeled as B.

- It is observed that usage of chunk label O is not jusitfied because sometimes it is assigned to
 - 1. Conjuctions, CC
 - 2. Punctuations
 - 3. Interrogative sentences (start word VBD)

2 Conditional Random Field

2.1 Results

1	1Precision	1Recall	1Fscore
В	0.96	0.96	0.96
I	0.94	0.94	0.94
O	0.95	0.96	0.96
Overall	0.95	0.95	0.95

Table 3: Tag wise metrics

2.2 Error Analysis

• Semantic analysis is required for some sentences like:

the	longer	the	warranty	,	the	longer	the	cutomer	
Ο	O	В	I	Ο	Ο	O	В	I	true
В	I	В	I	Ο	В	I	В	I	predicted

here , 'the longer' because of pos tags DT and VB , it is chunked as VP- DT VB Since , words like longer , shorter , smaller , larger are always labeled either as B or I in train data $P(O \mid these_words) = 0$ so ,classifier is not able to label them O.



 \bullet Very few occurences of some symbols like #

here , # being very less frequent , tagged as B in place of I , also $P(B \mid \#)$ is twice $P(I \mid \#).$

• Miclassification of words like haven't , aren't.

model is not able to learn these type of chunking

Since these occurs in two parts, not as a single word:

n't is miclassified as O inplace of I.

• Some abnormal assignment of O tags in test sentences:

example -Oregon general obligation won 100 million В O O O 0 ()O O В true T В I I I I Ι predicted

• Due to ambiguity in English for a word to be mostly tagged as noun and verb both, two chunk phrases NP VP are combined and predicted NP as whole.

The classifier performance on punctuation tags is improved to some extent as comapred to MEMM, but the problem still exist.

Like MEMM, CRF is also not able to learn usage of chunk label O.

Also the problem of comma being tagged as O in place of I also exists in MEMM , because there are two interpretation of comma example -

markets	,	investment	climate	and	management	practices .	
В	Ο	В	I	O	В	I	true
В	O	В	Ţ	Ţ	Ī	Ī	predicted

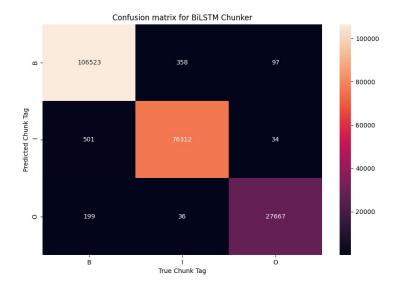
here , classifier chunked ('investment climate and management prectices') in one single chunk , inplace of combining it collectively with 'markets'.

3 Bi-LSTM:

3.1 Results

1	1Precision	1Recall	1F1score
В	0.99	0.99	0.99
I	0.99	0.99	0.99
O	0.99	0.99	0.99
Overall	0.99	0.99	0.99

Table 4: Tag wise metrics



3.2 Error Analysis

• Some sentences require semantic knowledge:

	The i	more .	, the more
True-	O	O	O O
Predicted-	В	Ι	, B I

'the' being DT , 'the more' is chunked as PP – DT P also $P(O \mid more) = 0.016$, very less as compared to that of B and I.

• Like CRF , bilstm is also suffered from words like can't ,doesn't ,year's

ca n't , does n't
True- O O O O Predicted- B I B I this is because
$$P(B \mid ca) = 1$$
 , $P(B \mid does) = 0.952$

• Wrong true lables in test sentences or abnormal test sentences

It can be observed that classifier predictions are actually correct.

• Bi-Lstm removed the problem of punctuations , O label with cunjuction .But O label with VBD problem still exists.

this is because , $P(B \mid could) = 0.979$, also 'imply' occur only 1 time in train and its pos-tag is VB and $P(I \mid VB) = 0.903$

Its performance is very high as compared to MEMM and CRF.