NLP Assignment 3: Named Entity Recognition with the Structured Perceptron

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1 Introduction

A Named Entity Recogniser (NER) with Structured Perceptron has been implemented. It is the process of labeling named-entities in the text. Named entities are real-world objects such as persons, locations, organisations etc, that can be denoted by a proper name.

2 Implementation

The following functions have been implemented keeping 5 iterations in mind to train the data:

- 1. load_dataset_sents: This is used to obtain word and tag sequences for each sentence.
- 2. merge_dictionaries: This is used to merge dictionaries.
- 3. **ngrams_generation**: This is used to generate n-grams.

List of ϕ_{-1} functions -

- 4. word_label_phi_1: This is used to return the counts of current word-current label.
- 5. sentence_label: This is used to break the training data into lists of sentences and labels.
- 6. **phi_1_func**: This is used to return the dictionary with counts of 'cw_cl_counts' keys in the given sentence.
- 7. **train**: This is used to train and return the weights.
- 8. **predict**: This is used return a predicted tag sequence for.
- 9. **test**: This is used to get the f1 measure.
- 10. **top_10**: This is used to get the top 10 for each tag.

Similar functions have been used for ϕ_2 , namely -

word_label_phi_2, phi_2_func, train_phi_2, predict_phi_2, test_phi_2 and top_10_phi_2.

3 Answers to the Questions

• F1 score Table:

Seed Value	$\Phi_{-}1$	$\Phi_{-}1 + \Phi_{-}2$
180128022	75.71%	73.83%

- These values make sense as the most of the named-entities are labelled correctly with an average accuracy of close to 75% for both the features.
- Yes, the differences among the feature sets in micro-F1 score are expected due to the difference between current word-current label and previous label-current label.
 - No, taking Bigram into account didn't improve the accuracy.

The accuracy is not increasing because ϕ_{-2} has more information about the feature sets and because of this high dimension, it is sparse, and as a result, the accuracy gets a little lower.

Tag_Value	1.4	1 2	3	1 4	5	1 6	1.7	8	9	10
ray_varue	-	1	3	1				0	9	10
0	1996-08-22 0	0	BORROWER 0	LAST_0	AA+_0	REOFFER 0	=_0	NOTES_0	S_0	SHORT_0
PER	Peter_PER	Colleen PER	Siegel_PER	Hassan_PER	Hafidh_PER	Hilary_PER	Gush_PER	Steve_PER	Stricker_PER	O'Meara_PER
LOC	BRUSSELS_LOC	LONDON_LOC	BEIJING_LOC	FRANKFURT_LOC	. –	TUNIS_LOC	BAGHDAD_LOC	MANAMA_LOC	DUBAI_LOC	IRAQ_LOC
ORG	BAYERISCHE_ORG	VEREINSBANK_ORG	S&P_ORG	THAWRA_ORG	AN-NAHAR_ORG	AS-SAFIR_ORG	AL-ANWAR_ORG	AD-DIYAR_ORG	NIDA'A_ORG	AL-WATAN_ORG
MISC	C\$_MISC	Canadian_MISC	Open_MISC	Malaysian_MISO	C League_MISC	Baseball_MISC	AMERICAN_MISC	LEAGUE_MISC	EASTERN_MISC	DIVISION_MISC
			Figure	1: Top 10 I	Features for	Feature Set	. Φ ₋ 1			
Tag Value	I 1	2	O	1: Top 10 I		Feature Set	,	8	I 9	I 10
Tag_Value	1	2	Figure	1	Features for 1 5 1	Feature Set	,	8	9 	10
	1 ,_0	2 from_0	O	1		6	7 	8	9 :_0	
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0 PER		from_0	3 AT_0	4 out_0	5 0-0_0	6 Friday_0 McEwen_PER	7 1-0_0 Fogarty_PER	Sunday_0	 :_0)_0
Tag_Value O PER LOC ORG	 ,_0 Slight_PER	from_0 Kocinski_PER	3 AT_0 Jim_PER	4 out_0 Corser_PER	5 0-0_0 Armstrong_PER	6 Friday_0 McEwen_PER Spain_LOC	7 1-0_0 Fogarty_PER	Sunday_0 Pau1_PER	 :_0 RPER)_0 Capiot_PER

Figure 2: Top 10 Features for Feature Set, $\Phi_{-}1 + \Phi_{-}2$