Better Chinese Word Segmentation using Dual Decomposition

Abstract

Cite (?).

1 Introduction

- CWS is essential for many downstream applications and its performance has direct impacts
- Two primary approaches: character-based and word-based
- Character based includes work like:
- Word based includes work like:
- In both cases out-of-vocabulary recall is a problem, but char-based sequence models win
- Solution has been proposed: mix models
- Existing work (Sun paper?) trains many models and uses voting
- We propose a simpler and more direct solution to model mixing: dual decomp to have two simultaneous mutually informative models

2 Methodology

- TODO: Work on this section together explain dual decomp in this context in a simple way
- proposal: if Rob can understand the methodology then your average non-dual-decomp expert will understand it

3 Experiments

3.1 Accuracy

- show that this model does better than existing work
- biggest win is on R_{oov}

3.2 Efficiency

- show that this model is faster / simpler / etc than existing work
- important that methodology section is clear enough that other people could implement this

	Recall	Precision	F_1	OOV	$R_{ m oov}$	R_{iv}
CRF	0.978	0.969	0.973	0.035	0.723	0.987
PCT	0.978	0.971	0.974	0.035	0.730	0.987
DD	0.981	0.973	0.977	0.035	0.741	0.989

Table 1: Results on CTB-6 dataset.

4 Conclusion

⁰This result would place 2nd in the SIGHAN competition.

SIGHAN 2005

	SIGNAN 2003											
		Recall	Precision	F_1	OOV	R_{oov}	R_{iv}					
AS	SIGHAN winner	0.952	0.951	0.952	0.043	0.696	0.963					
	CRF-Char	0.952	0.936	0.944	0.043	0.589	0.969					
	Perceptron-Word	0.958	0.950	0.954	0.043	0.695	0.970					
	Dual Decomp	0.959	0.949	0.954	0.043	0.677	0.972					
PKU	SIGHAN winner	0.953	0.946	0.950	0.058	0.636	0.972					
	CRF-Char	0.946	0.953	0.949	0.058	0.778	0.956					
	Perceptron-Word	0.941	0.955	0.948	0.058	0.767	0.952					
	Dual Decomp	0.948	0.957	0.953	0.058	0.787	0.958					
CITYU	SIGHAN winner	0.941	0.946	0.943	0.074	0.698	0.961					
	CRF-Char	0.947	0.940	0.943	0.074	0.761	0.962					
	Perceptron-Word	0.943	0.940	0.942	0.074	0.717	0.961					
	Dual Decomp	0.950	0.944	0.947	0.074	0.753	0.965					
	SIGHAN winner	0.962	0.966	0.964	0.026	0.717	0.968					
MCD	CRF-Char	0.964	0.966	0.965	0.026	0.713	0.971					
MSR	Perceptron-Word	0.970	0.972	0.971	0.026	0.746	0.976					
	Dual Decomp	0.973	0.974	0.974	0.026	0.760	0.979					
		SIG	HAN 2003									
	SIGHAN winner	0.966	0.956	0.961	0.022	0.364	0.980					
AS	CRF-Char	0.969	0.969	0.969	0.022	0.748	0.974					
	Perceptron-Word	0.967	0.967	0.967	0.022	0.729	0.972					
	Dual Decomp	0.970	0.971	0.971	0.022	0.775	0.975					
	SIGHAN winner	0.962	0.940	0.951	0.069	0.724	0.979					
DIZI	CRF-Char	0.954	0.952	0.953	0.069	0.803	0.965					
PKU	Perceptron-Word	0.949	0.952	0.950	0.069	0.790	0.960					
	Dual Decomp	0.954	0.954	0.954	0.069	0.806	0.965					
CITYU	SIGHAN winner	0.947	0.934	0.940	0.071	0.625	0.972					
	CRF-Char	0.944	0.939	0.941	0.071	0.741	0.959					
	Perceptron-Word	0.944	0.945	0.945	0.071	0.730	0.960					
	Dual Decomp	0.950	0.949	0.949	0.071	0.754	0.965					
СТВ	SIGHAN winner	0.886	0.875	0.881	0.181	0.644	0.927					
	CRF-Char	0.869	0.865	0.867	0.181	0.680	0.910					
	Perceptron-Word	0.865	0.871	0.868	0.181	0.660	0.910					
	Dual Decomp	0.876	0.878	0.877^{0}	0.181	0.692	0.917					

Table 2: Results on SIGHAN 2005 and 2003 datasets.