Linguistic Structure Prediction

49c24dbf57a9a262d0eb858701dff4a3 ebrary

Noah A. Smith

49c24dbf57a9a262d0eb858701dff4a3

Synthesis Lectures on Human Language Technologies

Graeme Hirst, Series Editor

ebrary	
	49c24dbf57a9a262d0eb858701dff4a3 ebrary
49c24dbf57a9a262d0eb858701dff4a3	
ebrary	
	49c24dbf57a9a262d0eb858701dff4a3 ebrary
th, Noah A Synthesis Lectures on Human Language Technologies : Linguistic Stru	ucture Prediction.

Smith, Noah A.. Synthesis Lectures on Human Language Technologies: Linguistic Structure Predictions and Claypool Publishers, . p 2
http://site.ebrary.com/id/10573628?ppg=2
Copyright © Morgan & Claypool Publishers. . All rights reserved.
May not be reproduced in any form without permission from the publisher, except fair uses permitted under U.S. or applicable copyright law.

49c24dbf57a9a262d0eb858701dff4a3 ebrary

Linguistic Structure Prediction

49c24dbf57a9a262d0eb858701dff4a3 ebrary

Synthesis Lectures on Human Language Technologies

Editor

49c24dbf57a9a262d0eb858701dff4a

Graeme Hirst, University of Toronto

The series consists of 50- to 150-page monographs on topics relating to natural language processing, computational linguistics, information retrieval, and spoken language understanding. Emphasis is on important new techniques, on new applications, and on topics that combine two or more HLT subfields.

Linguistic Structure Prediction

Noah A. Smith 2011

Learning to Rank for Information Retrieval and Natural Language Processing

Hang Li 2011

Computational Modeling of Human Language Acquisition

Afra Ålishahi 2010

Introduction to Arabic Natural Language Processing

Nizar Y. Habash 2010

Cross-Language Information Retrieval

Jian-Yun Nie

2010

Automated Grammatical Error Detection for Language Learners Claudia Leacock, Martin Chodorow, Michael Gamon, and Joel Tetreault

Data-Intensive Text Processing with MapReduce

Jimmy Lin and Chris Dyer

2010

iii

Semantic Role Labeling

Martha Palmer, Daniel Gildea, and Nianwen Xue 2010

Spoken Dialogue Systems

Kristiina Jokinen and Michael McTear 2009

Introduction to Chinese Natural Language Processing

Kam-Fai Wong, Wenjie Li, Ruifeng Xu, and Zheng-sheng Zhang 2009

49c24dbf57a9a262d0eb858701dff4a3

Introduction to Linguistic Annotation and Text Analytics

Graham Wilcock 2009

Dependency Parsing

Sandra Kübler, Ryan McDonald, and Joakim Nivre 2009

Statistical Language Models for Information Retrieval

ChengXiang Zhai 2008

49c24dbf57a9a262d0eb858701dff4a3 ebrary

Copyright @ 2011 by Morgan & Claypool

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted in any form or by any means—electronic, mechanical, photocopy, recording, or any other except for brief quotations in printed reviews, without the prior permission of the publisher.

Linguistic Structure Prediction

Noah A. Smith

www.morganclaypool.com

ISBN: 9781608454051 paperback ISBN: 9781608454068 ebook

DOI 10.2200/S00361ED1V01Y201105HLT013

A Publication in the Morgan & Claypool Publishers series SYNTHESIS LECTURES ON HUMAN LANGUAGE TECHNOLOGIES

Lecture #13

49c24dbf57a9a262d0eb85 ebrary

Series Editor: Graeme Hirst, University of Toronto Series ISSN

Synthesis Lectures on Human Language Technologies

Print 1947-4040 Electronic 1947-4059

Linguistic Structure Prediction

49c24dbf57a9a262d0eb858701dff4a3

Noah A. Smith Carnegie Mellon University

49c24dbf57a9a262d0eb858701dff4a3 ebrary

SYNTHESIS LECTURES ON HUMAN LANGUAGE TECHNOLOGIES #13



ABSTRACT

A major part of natural language processing now depends on the use of text data to build linguistic analyzers. We consider statistical, computational approaches to modeling linguistic structure. We seek to unify across many approaches and many kinds of linguistic structures. Assuming a basic understanding of natural language processing and/or machine learning, we seek to bridge the gap between the two fields. Approaches to decoding (i.e., carrying out linguistic structure prediction) and supervised and unsupervised learning of models that predict discrete structures as outputs are the focus. We also survey natural language processing problems to which these methods are being applied, and we address related topics in probabilistic inference, optimization, and experimental methodology.

KEYWORDS

natural language processing, computational linguistics, machine learning, decoding, supervised learning, unsupervised learning, structured prediction, probabilistic inference, statistical modeling

49c24dbf57a9a262d0eb858701dff4a3 ebrary

> 49c24dbf57a9a262d0eb858701dff4a3 ebrary

vii

Contents

	Preface		
	Ackı	nowledgments	
		49c24dbf57a9a262d0eb858701df	
1	Repr	resentations and Linguistic Data	
	1.1	Sequential Prediction	
	1.2	Sequence Segmentation	
	1.3	Word Classes and Sequence Labeling	
		1.3.1 Morphological Disambiguation	
		1.3.2 Chunking	
	1.4	Syntax	
	1.5	Semantics	
	1.6	Coreference Resolution	
	1.7	Sentiment Analysis	
	1.8	Discourse	
	1.9	Alignment	
	1.10	Text-to-Text Transformations	
	1.11	Types	
	1.12	Why Linguistic Structure is a Moving Target	
9c24dbf57a9a262d0el brary	81.13	Conclusion	
2	Deco	oding: Making Predictions	
	2.1	Definitions	
	2.2	Five Views of Decoding	
		2.2.1 Probabilistic Graphical Models	
		2.2.2 Polytopes	
		2.2.3 Parsing with Grammars	
		2.2.4 Graphs and Hypergraphs	
		2.2.5 Weighted Logic Programs	
	2.3	Dynamic Programming	
		2.3.1 Shortest or Minimum-Cost Path	

viii

	VIII			
			2.3.2 Semirings	48
			2.3.3 DP as Logical Deduction	50
			2.3.4 Solving DPs	55
			2.3.5 Approximate Search	61
			2.3.6 Reranking and Coarse-to-Fine Decoding	64
		2.4	Specialized Graph Algorithms	64
			2.4.1 Bipartite Matchings	65
			2.4.2 Spanning Trees	65
			2.4.3 Maximum Flow and Minimum Cut .49c24dbf57c9a262dGeb85870	664
		2.5	Conclusion	67 ^{ebr}
	3	Learn	ing Structure from Annotated Data	69
		3.1	Annotated Data	69
		3.2	Generic Formulation of Learning	70
		3.3	Generative Models	71
			3.3.1 Decoding Rule	73
			3.3.2 Multinomial-Based Models	73
			3.3.3 Hidden Markov Models	74
			3.3.4 Probabilistic Context-Free Grammars	78
			3.3.5 Other Generative Multinomial-Based Models	78
			3.3.6 Maximum Likelihood Estimation By Counting	79
			3.3.7 Maximum A Posteriori Estimation	81
			3.3.8 Alternative Parameterization: Log-Linear Models	83
			3.3.9 Comments	85
		3.4	Conditional Models	86
9c24dbf57a9a262d0 brary	eb8587	3.5dff	Globally Normalized Conditional Log-Linear Models	88
brary			3.5.1 Logistic Regression	88
			3.5.2 Conditional Random Fields	89
			3.5.3 Feature Choice	91
			3.5.4 Maximum Likelihood Estimation	92
			3.5.5 Maximum A Posteriori Estimation	94
			3.5.6 Pseudolikelihood	97
			3.5.7 Toward Discriminative Learning	98
		3.6	Large Margin Methods	99
			3.6.1 Binary Classification	99
			3.6.2 Perceptron	101
			3.6.3 Multi-class Support Vector Machines	103

			ix	
		3.6.4 Structural SVM	104	
		3.6.5 Optimization	105	
		3.6.6 Discussion	106	
	3.7	Conclusion	106	
4	Learn	ing Structure from Incomplete Data	109	
	4.1	Unsupervised Generative Models	110	
		4.1.1 Expectation Maximization		
		4.1.2 Word Clustering		
		4.1.3 Hard and Soft K-Means		bra
		4.1.4 The Structured Case	117	
		4.1.5 Hidden Markov Models	119	
		4.1.6 EM Iterations Improve Likelihood	120	
		4.1.7 Extensions and Improvements		
		4.1.8 Log-Linear EM		
		4.1.9 Contrastive Estimation		
	4.2	Bayesian Unsupervised Learning		
		4.2.1 Empirical Bayes		
		4.2.2 Latent Dirichlet Allocation		
		4.2.3 EM in the Empirical Bayesian Setting		
		4.2.4 Inference		
		4.2.5 Nonparametric Bayesian Methods	134	
		4.2.6 Discussion		
	4.3	Hidden Variable Learning	140	
		4.3.1 Generative Models with Hidden Variables		
9c24dbf57a9a262d0eb8	358701	4.3.2 Conditional Log-Linear Models with Hidden Variables	142	
brary		4.3.3 Large Margin Methods with Hidden Variables		
	4.4	Conclusion	145	
5	Beyon	d Decoding: Inference	147	
	5.1	Partition Functions: Summing over y	148	
		5.1.1 Summing by Dynamic Programming		
		5.1.2 Other Summing Algorithms		
	5.2	Feature Expectations		
		5.2.1 Reverse DPs		
		5.2.2 Another Interpretation of Reverse Values		
		5.2.3 From Reverse Values to Expectations		

49c24dbf57a9a262d0eb858701dff4a3 ebrary

5.3 5.4 5.5 5.6 A The Hill-Climbing Analogy.....49c24dbf57a9a262d0eb858701dff4a3 A.2 A.3 A.4 A.5 A.6 B B.1 B.1.2 Cross-Validation 183 49c24dbf57a9a262d0eb858701dff B.2 \mathbf{C}

		XI	
Loc	ally Normalized Conditional Models	203	
D.1	Probabilistic Finite-State Automata	203	
D.2	Maximum Entropy Markov Models	204	
D.3	Directional Effects	205	
D.4	Comparison to Globally Normalized Models	206	
D.5	Decoding	207	
D.6	Theory vs. Practice	208	
Bib	liography	2097	1dff4a3 ebrary
Aut	hor's Biography	241	

49c24dbf57a9a262d0eb858701dff4a3 ebrary

> 49c24dbf57a9a262d0eb858701dff4a3 ebrarv

49c24dbf57a9a262d0eb858701dff4a3 ebrary	
	49c24dbf57a9a262d0eb858701dff4a3 ebrary
49c24dbf57a9a262d0eb858701dff4a3	
ebrary	
	49c24dbf57a9a262d0eb858701dff4a3 ebrary