

Course Overview

CSC2540S Machine Learning and Universal Grammar
Department of Computer Science, University of Toronto

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January 6, 2009

Outline

- 1 Structure of the Course
- 2 Course Evaluation
- 3 Universal Grammar and Linguistic Nativism
- 4 Finite Hypothesis Spaces and Grammar Induction
- 5 A Radically Reduced UG
- 6 Conclusions

Topics and Schedule

Week 1: January 6, 2009

- Overview of the problem
- The argument from the poverty of stimulus (APS) and Universal Grammar

Week 2: January 13

- Nativism and cognitive architecture
- The evolution of language

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Week 3: January 20

- Clarifying the APS
- Some linguistic arguments for the APS

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- The nature of primary linguistic evidence (PLD)
- The role of negative evidence in language acquisition

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- An alternative computational learning model: PAC learning

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Week 7: February 17

- Reading Week

Week 8: February 24

- Modifying PAC: Using probability distributions on learning samples

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- Unsupervised grammar induction
- Recent work on acquiring grammars through the application of machine learning methods to large natural language corpora

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- Parameters in linguistic theory and in probabilistic language models
- A bootstrapping approach to parameter estimation for language models

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Week 11: March 17

- The FOXP2 Gene and specific language impairment (SLI)
- Psychological evidence for Bayesian grammar induction

Weeks 12-14: March 24, March 31, and April 7

- Project presentations

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The Course Grade

- Course assessment depends upon
 - (a) a project, which will provide 80% of the final grade, and
 - (b) class participation, which counts for 20% of the grade.
- For the project
 - (a) you can write a term paper, or
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Term Paper

- A term paper should be 5000-8000 words in length.
- It must provide an in depth critical study of one or more of the issues taken up in the course.
- The paper should discuss salient parts of the literature relevant to the issues it addresses.
- It need not offer a new proposal.
- However, a paper defending an original hypothesis with interesting arguments is, of course, welcome.

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Programming Project

- An implemented system must be relevant to the course.
- It should illustrate some of the computational learning questions that we discuss.
- The program can be a small scale prototype learning algorithm rather than a wide coverage corpus system.
- It must be an original piece of work developed for this course.
- A system demo will be given in class.
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Domain General and Domain Specific Learning Mechanisms

- The APS has been invoked as the primary motivation for a strong version of linguistic nativism.
- It posits a distinct language faculty with innate learning biases for language acquisition.
- This type of cognitive nativism is distinct from the claim that human cognitive activity depends on a rich set of innate learning priors.
- The former posits strong domain specific learning biases, while the latter allows for the possibility that most (all?) types of learning are achieved through domain general procedures, initialized for specific functions.

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Chomsky on Statistical Modeling of Grammar

- Chomsky (1957) rejects the use of statistical methods to represent the distinction between grammatical and ungrammatical strings.
 - ① Colourless green ideas sleep furiously.
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- (1) and (2) both have a probability approaching nil (in 1957) of appearing in a corpus or actual speech.
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Chomsky (1957) (p. 17)

If we rank the sequences of a given length in order of statistical approximation to English, we will find both grammatical and ungrammatical sequences scattered throughout the list; there appears to be no particular relation between order of approximation and grammaticalness. Despite the undeniable interest and importance of semantic and statistical studies of language, they appear to have no direct relevance to the problem of determining or characterizing the set of grammatical utterances. I believe that we are forced to conclude that grammar is autonomous and independent of meaning, and that probabilistic models give no particular insight into some of the basic problems of syntactic structure.

A Smoothed Bigram Model

- Chomsky moves from the claim that information theoretic methods cannot identify the set of grammatical sentences in the PLD to the conclusion that they are irrelevant to characterizing syntactic structure.
- This argument is not sound.
- Chomsky assumes a bigram model in which probability of a word in a string depends on the word that immediately precedes it.
- Pereira (2000) constructs a smoothed bigram model in which the probability of a word depends on the class of the prior word.

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- Pereira's model computes the conditional probability of a word w_i in a string with the formula

$$P(w_i | w_{i-1}) \approx \sum_c P(w_i | c)P(c | w_{i-1})$$

where c is the class of w_{i-1} .

- We can use distributional patterns of words in a corpus to learn their classes from training data.
- Other procedures allow us to compute the values of the parameters $P(w_i | c)$ and $P(c | w_{i-1})$ from this data.
- When applied to (1) and (2), this model yields a five order of magnitude difference between their probability values for a corpus of newspaper text.

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- UG(1) An enumeration of the class s_1, s_2, \dots of possible sentences (**set of strings that each grammar generates**)
- UG(2) An enumeration of the class SD_1, SD_2, \dots of possible structural descriptions (**the set of syntactic representations that these grammars assign to the strings that they produce**)
- UG(3) An enumeration of the class G_1, G_2, \dots of possible generative grammars (**the hypothesis space of possible grammars for natural languages**)
- UG(4) Specification of a function f such that $SD_{f(i,j)}$ is the structural description assigned to sentence s_i by grammar G_j , for arbitrary i, j (**the function that maps a grammar to the set of representations for a string**)
- UG(5) Specification of a function m such that $m(i)$ is an integer associated with the grammar G_i as its value (with, let us say, lower value indicated by higher number) (**an evaluation measure that ranks the possible grammars**)

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- By assumption, it ranks grammars that enjoy the same degree of descriptive adequacy, and so it is not accessible to PLD.

Problems with the Evaluation Measure

- Notions of formal simplicity of the sort used to choose among rival scientific theories do not offer an appropriate grammar ranking procedure because
 - (i) they are notoriously difficult to formulate as global metrics that are both precise and consistent, and
 - (ii) if one could define a workable simplicity measure of this kind, then it would not be part of a domain specific UG.
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Government Binding (GB) and the Principles and Parameters (P&P) Model of UG

- Chomsky (1981): UG consists of schematic constraints on the representations in a syntactic derivation of a sentence, and on the movement operation which maps between adjacent levels in the derivation.
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Language Acquisition as Parameter Setting

- Language acquisition consists in setting parameter values through exposure to a small amount of data from a language.
- UG contains a limited number of principles with a bounded set of parameters, each taking a restricted range of possible values.
- Therefore it defines a finite set of possible (core) grammars for natural language.
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Finite Hypothesis Spaces and the Tractability of Learning

- Chomsky (1981): the finiteness property of the P&P model of UG "trivializes" important aspects of grammar induction.
- In fact, a finite hypothesis space is neither a necessary nor a sufficient condition for efficient learning.
- Grammar induction in a finite hypothesis space can be intractable.
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UG in the Minimalist Program

- The Minimalist Program (MP) (Chomsky 1995, 2001, 2005, 2007) eliminates intermediate derivational levels of representation (D- and S-Structure in the GB model).
- Only the two interface levels of LF (Logical Form, the Conceptual-Intentional interface) and PF (Phonetic Form, the Sensory Motor interface) remain, as the outputs of a syntactic derivation from a selection of lexical items (a numeration).
- A single operation, Merge, combines lexically projected functional heads with their complements and their adjuncts to produce a hierarchical tree structure.

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Syntactic Derivations and Interface Representations

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- Movement is triggered by the need to check features in the lexical head of a constituent against those in the target site.
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UG as a Perfect Computational System

- The guiding principle behind the MP is that UG is a "perfect" computational system.
- It provides an optimal mapping from a lexical numeration to the two interface levels of LF and PF.
- Like the grammar evaluation measure of the *Aspects* model, these notions of perfection and optimality are not characterized independently of the theory of grammar that they are intended to motivate.
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Parameters in the MP

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- In the MP they have been moved to the functional heads of the lexicon.
- In fact Boeckx (2008) proposes eliminating parameters from "narrow syntax" entirely.
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Language Acquisition in a Reduced UG

- The MP is a drastic retreat from the rich domain specific mechanisms of previous theories.
- Chomsky argued that these elaborate devices were required because domain general procedures could not overcome the poverty of PLD for language acquisition.
- The current theory fades into an application of procedures shared with other cognitive capacities.
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