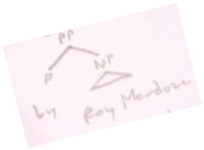
'Ideal Learning' of Natural Language: Positive Results about Learning from Positive Evidence



Ray Mendoza
Psych 245A
Thursday, April 24th, 2008

Outline

- Ideal Learner
- Ideal Language Learning by Simplicity
- The Prediction Theorem and Ideal Language Learning
- The Ideal Learning of Grammaticality Judgements
- The Ideal Learning of Language Production
- The Poverty of Stimulus Reconsidered
- Summary

Ideal Learner

- Propose an ideal learner
- Problem 1: Logical Problem of Lang. Acq.
  - Cannot learn from only positive data
  - Assumes negative linguistic data is non-critical (and non-existent)
- Problem 2: Baker's Paradox
  - Specific constructions cannot be learned
  - Considers learnability from a construction-specific perspective
- Learner follows *Simplicity Principle* (i.e. Occam's Razor)
- Chater/Vitanyi: "you can learn given an *ideal learner*, but this does *not* mean a child can" (child != ideal learner)

Ideal Language Learning by Simplicity

- Four components
  - Class of Linguistic inputs (enviroment)
  - Class of possible models of language (linguistic structure)
  - Measure of learning performance
  - Learning model

Class of Linguistic Inputs

- Potentially Infinite
- Represented as a binary string
- Produced by a *real computational process*
- Combined with *random input* → explains effect of non-deterministic input to learner
- Modeled with
  - Monotone Turing machine
  - Random input to the machine
- Random *programming* monkeys ex.

Class of Possible Models of Language

- Gold's Theorem: Only provides for *identification*
- Chomsky's context-free languages: principles and parameters framework
- *The model of linguistic data* must be generated by a computable process
  - Rules must have a mechanism by which they are learned
  - Movement must have a mechanism
  - All linguistic constructs must be *learned*
  - (perhaps this will one day give feedback into linguistic theory!)

Measuring Learning Performance

- Primary measure: prediction
  - Can we predict the continuation of utterances
  - Adds another level of complexity to learning

$\mu_C(0|x) = \mu_C(x0) / \mu_C(x)$ prob. of 0 given x

- Learner doesn't know true distribution of μ_C

The Learning Method: Predicting by Simplicity

- Simplistic explanation of data preferred
- Considers predictions from various hypothesizes
- Applies theory which generates simplest encoding of data (consistent with data)

consistency ← ?!? → simplicity

- We favor *shortest encoding of data* (based on Kolmogorov complexity)

The Learning Method: Predicting by Simplicity

- "By using a universal programming language, the learner can be sure to be able, at least in principle, to represent every such computational process."
- Issues
  - Encoding length varies among different 'universal programming' languages
  - Length of encoding has depends on the mental representations (we must presuppose this to begin with!)
- Encodings (choose your poison)

  phrase structure

  tree-adj. grammar < Minimalist Program < Govt. & Binding

  categorical grammar

The Prediction Theorem and Ideal Language Learning

- Prediction Theorem
  - Given a universal monotone distribution

    λ : universal monotone distribution (target)

    μ : computable monotone distribution (learned)

    $\lambda(0|x) = \lambda(x0) / \lambda(x)$ prediction

    $\text{Error}(x) = (\lambda(0|x) - \mu(0|x))^2$ error

    $S_n = \Sigma\, \mu(x)\, \text{Error}(x)$ weighted error

    $\Sigma_{j=1\ldots\infty} S_j$ all weighted error

    $\Sigma_{j=1\ldots\infty} S_j \leq (\log_e 2 / 2)\, K(\mu)$
- In the limit, error is bounded (and in some sense minimized)

The Ideal Learning of Grammaticality Judgements

- Discusses asymptotic behavior of overgeneralization and undergeneralization
- Learners overgeneralize

  $\Delta_j(x) = \sum P_\lambda(k|x)$ error prob. of jth symbol

  Does not account for phrasal structure in probabilities

  $\langle\Delta_j\rangle = \sum P_\lambda(k|x)\, \Delta_j(x)$ average

  $\sum \langle\Delta_j\rangle \leq K(\mu) / \log_e 2$ bounds all avg. err.

The Ideal Learning of Grammaticality Judgements

- Learners undergeneralize in practice
- Under Simplicity Principle, this should *not* happen
  - More general explanations which account for more data are preferred over special cases which leading to idiosyncrasies
- Soft undergeneralization

  $\Lambda_j(x) = \sum P_\mu(k|x)$ prob of accurate prediction of prob. dist P_λ

  Does not account for phrasal structure in probabilities

  $\langle\Lambda_j\rangle = \sum P_\mu(k|x)\, \Lambda_j(x)$ weighted average

  $\sum \langle\Lambda_j\rangle \leq K(\mu) / \log_2(f/e)$ bound prob. of soft generalization

The Ideal Learning of Language Production

- Acquisition also comprises of production
- Learned distribution approaches univ. dist.

$\lambda(y|x) / \mu(y|x) \rightarrow 1$ conv. of prob. distns

Thus, using learned distribution for production ensures mutual (native) intelligibility

The Poverty of Stimulus Reconsidered

- Constraint-based systems complicate productive grammar, but constraints "can be learned given enough positive data" (needs to be fleshed out)
- Identification in the limit, we (last time) concluded is inapplicable, in general, to language acquisition
  - His problem is identification, not learning
- Statistical properties of language, bivalence of grammaticality judgements (probabilistic models of language reception/production)
- Absence as implicit negative evidence

Summary

- Defined simplistic learner
- Convergence of predictive capabilities
- Convergence of grammaticality judgement
- Convergence of language production
- Language is learnable from positive input

Questions