Online Entropy-based Model of Lexical Category Acquisition

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Outline

Human category acquisition

- Humans incrementally learn lexical categories from exposure to language
  - Children form robust lexical categories early on [Gelman and Taylor, 1984, Kemp et al., 2005]
- Distributional properties of words provide cues about its category
  - Children are sensitive to co-occurrence statistics [Aslin et al., 1998]
  - Child-directed speech provides contextual evidence for learning categories [Redington et al., 1998, Mintz, 2002]

Unsupervised category induction

- Many unsupervised models use distributional information to learn categories
  - [Brown et al., 1992, Clark, 2003, Goldwater and Griffiths, 2007]
- But most are not cognitively plausible
  - process data in batch mode
  - categorize word types instead of word tokens
  - pre-define the number of categories

Online category induction

- A few online models of category induction are proposed
  - [Cartwright and Brent, 1997, Parisien et al., 2008]
  - More cognitively motivated
- But may require large amounts of training, and be over-sensitive to context variation
- We propose
  - A simple algorithm which incrementally learns an unbounded number of categories
  - A task-based approach to evaluating human categorization models

Outline

1. Lexical category acquisition in humans
2. Online information-theoretic model
3. Task-based evaluation

Informativeness versus parsimony

- A good categorization model partitions words into discrete categories such that:
  - The number and distribution of categories is as simple as possible
  - Categories are highly informative about their members
- In other words trade-off parsimony against informativeness (goodness-of-fit)

Joint entropy criterion

- Parsimony

$$H(Y) = -\sum_{i=1}^{N} P(Y = y_i) \log_2[P(Y = y_i)] \qquad (1)$$

- Informativeness

$$H(X|Y) = \sum_{i=1}^{N} P(Y = y_i) H(X|Y = y_i) \qquad (2)$$

- Joint entropy minimizes the sum of both

$$H(X,Y) = H(Y) + H(X|Y) \qquad (3)$$

Joint minimization for multiple variables

Optimize simultaneously for all features

$$\sum_{j=1}^{M} H(X_j, Y) = \sum_{j=1}^{M} \left[H(X_j|Y) + H(Y) \right] \tag{4}$$

$$= \sum_{j=1}^{M} \left[H(X_j|Y) \right] + M \times H(Y)$$

Incremental updates

- At point t find the best assignment $Y = y_i$:

$$\hat{y} = \begin{cases} y_{N+1} & \text{if } \forall y_n [\Delta H^t_{y_{N+1}} \leq \Delta H^t_{y_n}] \\ \operatorname{argmin}_{y \in \{y\}_{i=1}^N} \Delta H^t_y & \text{otherwise} \end{cases} \quad (5)$$

where

$$\Delta H^t_y = \sum_{j=1}^{M} \left[H^t_y(X_j, Y) - H^{t-1}(X_j, Y) \right] \quad (6)$$

- $H^t(X_j, Y)$ can be computed incrementally.

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Data

- Manchester portion of CHILDES, mothers' turns
- Discard one-word sentences and punctuation

Data Set	Sessions	#Sentences	#Words
Training	26–28	22,491	125,339
Development	29–30	15,193	85,361
Test	32–33	14,940	84,130

Labeling with categories

ΔH. Categories induced from the training set

Features:

want␣to	try	them␣on

PoS. POS tags from the Manchester corpus

Words. Word types

Parisien. Categories induced by Bayesian model of [Parisien et al., 2008] from the training set.

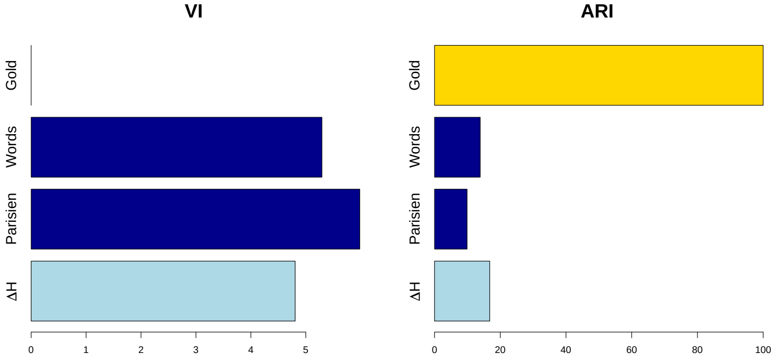
Example clusters

How to evaluate induced categories?

- Against gold POS tags
  - Arbitrary choice of granularity and/or criteria for membership
- Task based evaluation
  - Different tasks may call for different category representations
- Proposal: evaluate on a number tasks, simulating key aspects of human language processing

Evaluation against POS labels

- Variation of Information:
  $VI(X, X') = H(X) + H(X') - 2I(X, X')$
- Adjusted Rand Index



Task-based evaluation

- Word prediction
  - Guess a missing word based on its sentential context
- Semantic feature prediction
  - Predict the semantic properties of a novel word based on context
- Grammaticality judgement
  - Assess the syntactic well-formedness of a sentence based on the category labels assigned to its words

Word prediction

Human subjects are remarkably accurate at guessing words from context, e.g. in Cloze Test:

Petroleum, or crude oil, is one of the world's (1) —— natural resources. Plastics, synthetic fibres, and (2) —— chemicals are produced from petroleum. It is also used to make lubricants and waxes. (3) —— , its most important use is as a fuel for heating, for (4) – — electricity, and (5) —— for powering vehicles.

A. as important
B. most important
C. so importantly
D. less importantly
E. too important

Word prediction

Reciprocal rank

want to | put | them on

Word prediction

Reciprocal rank

want	to	put y_{123}	them	on	y_{123}	make take put get sit eat let

$$rank^{-1} = \frac{1}{3}$$

Word prediction: variants

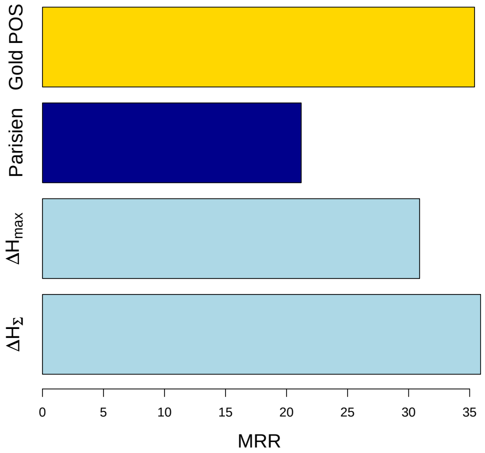
- $\Delta H_{\max}$

$$P(w|h) = P(w|\operatorname*{argmax}_i R(y_i|h)^{-1})$$

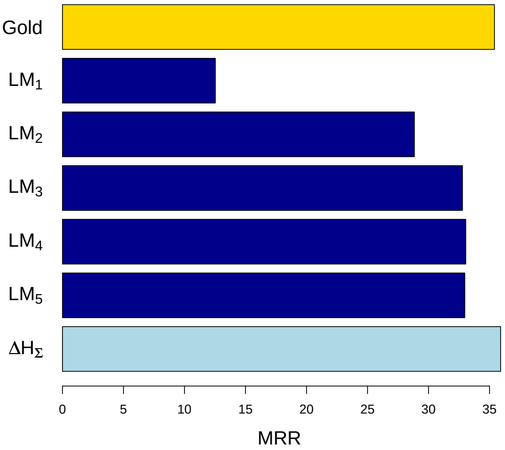
- ΔH_{Σ}

$$P(w|h) = \sum_{i=1}^{N} P(w|y_i) \frac{\mathrm{R}(y_i|h)^{-1}}{\sum_{i=1}^{N} \mathrm{R}(y_i|h)^{-1}}$$

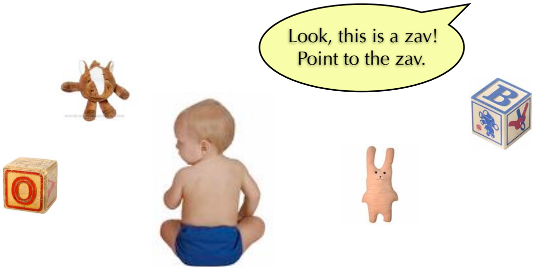
Word prediction: Results



Comparison to n-gram language models



Predicting semantic properties

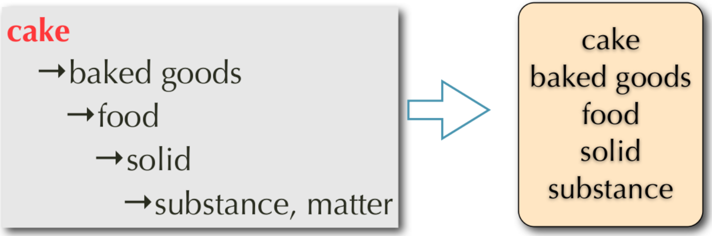


[Gelman and Taylor, 1984]: 2-year-olds treat words preceded by a determiner ("the zav") as common nouns, and interpret them as category members (block-like toy).

Predicting semantic properties

[Gelman and Taylor, 1984]: 2-year-olds treat words not preceded by a determiner ("Zav") as proper nouns, and interpret them as individuals (animal-like toy).

Semantic features from WordNet and VerbNet



WordNet hypernyms for cake **Semantic profile for cake**

Semantic profile for each category is the multiset union of the semantic sets of its members

Semantic feature prediction task

I had | cake | for lunch

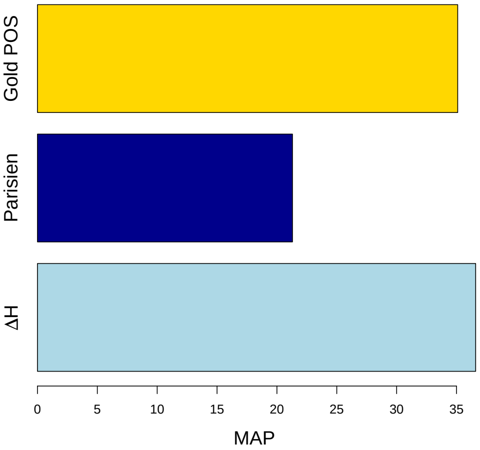
Semantic feature prediction task

I had | cake y_{123} | for lunch

$$\mathrm{AP}\left(\begin{array}{c|l|} y_{123} & \text{entity} \\ & \text{substance} \\ & \text{matter} \\ & \text{food} \\ & \text{edible} \\ & \ldots \end{array} \;,\; \left\{ \begin{array}{l} \text{cake} \\ \text{baked goods} \\ \text{food} \\ \text{solid} \\ \text{substance} \end{array} \right\} \right)$$

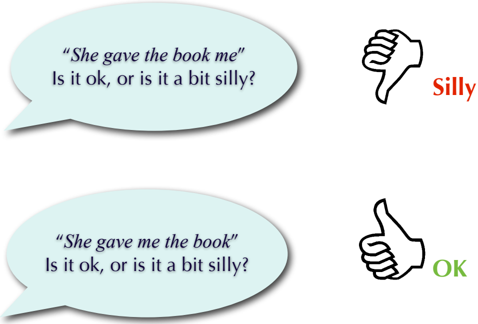
$$\mathrm{AP}(F, R) = \frac{1}{|R|} \sum_{r=1}^{|F|} P(r) \times \mathbf{1}_R(F_r) \quad (7)$$

Predicting semantic properties: Results



Grammaticality judgement

Both children and adults have a reliable concept of what is grammatical [Theakston, 2004]:



Grammaticality task

$$score(\mathbf{y}) = \min_{i=1}^{n} P(y_i | y_{i-2}, y_{i-1})$$

want to put them on

Grammaticality task

$$score(\mathbf{y}) = \min_{i=1}^{n} P(y_i | y_{i-2}, y_{i-1})$$

want	to	put	them	on
y_{41}	y_{21}	y_{123}	y_2	y_3

Grammaticality task

$$score(\mathbf{y}) = \min_{i=1}^{n} P(y_i | y_{i-2}, y_{i-1})$$

want	to	put	them	on	
y_{41}	y_{21}	y_{123}	y_2	y_3	
0.02	0.1	0.05	0.01	0.03	$= 0.0100$

Grammaticality task

$$score(\mathbf{y}) = \min_{i=1}^{n} P(y_i | y_{i-2}, y_{i-1})$$

want	to	put	them	on	
y_{41}	y_{21}	y_{123}	y_2	y_3	
0.02	0.1	0.05	0.01	0.03	$= 0.0100$

want	to	them	put	on	
y_{41}	y_{21}	y_{124}	y_4	y_3	
0.02	0.1	0.001	0.0005	0.005	$= 0.0005$

Grammaticality task

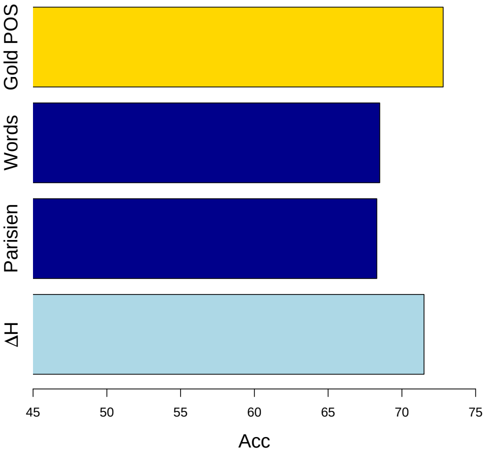
$$score(\mathbf{y}) = \min_{i=1}^{n} P(y_i | y_{i-2}, y_{i-1})$$

want	to	put	them	on	
y_{41}	y_{21}	y_{123}	y_2	y_3	
0.02	0.1	0.05	0.01	0.03	$= 0.0100$

want	to	them	put	on	
y_{41}	y_{21}	y_{124}	y_4	y_3	
0.02	0.1	0.001	0.0005	0.005	$= 0.0005$

$$correct = \begin{cases} 1 & \text{if } score(\mathbf{y}^{\text{ok}}) > score(\mathbf{y}^*) \\ 0 & \text{otherwise} \end{cases}$$

Grammaticality judgement: Results



Summary of results

	Gold	**Words**	**Parisien**	$\Delta \mathrm{H}_{\max}$	$\Delta \mathrm{H}_{\Sigma}$
Pred	0.354	-	0.212	0.309	**0.359**
Sem	0.351	-	0.213	**0.366**	-
Gram	**0.728**	0.685	0.683	0.715	-

Conclusion

- Learning categories
  - Categories can be learned from usage data incrementally
  - A simple online information-theoretic approach works well in this scenario
- Evaluation
  - Automatically induced categories can work better than PoS tags in language tasks
  - Evaluation of unsupervised category induction models should not rely exclusively on gold POS labels
- Future directions
  - Compare the performance of the model to humans
  - Develop a wider range of tasks

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Cluster evaluation metrics

- Variation of information:
  $VI(X;Y) = H(X) + H(Y) - 2I(X,Y)$
- Rand Index: R $= \frac{a+b}{a+b+c+d} = \frac{a+b}{\binom{n}{2}}$
- Adjusted Rand Index:
  $AdjustedIndex = \frac{Index - ExpectedIndex}{MaxIndex - ExpectedIndex}$