Computational Models of Sentence Processing and Syntactic Acquisition

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Introduction

Why study language computationally?

Both humans and computers can “learn” and “process” language

Unlike human subjects, we have more control over computers

- Input data, architecture, and training objective
- Thorough inspection of model predictions

How can we use computational modeling to shed light on human language processing and acquisition?

Roadmap

Modeling sentence processing with left-corner parsing (Oh, Clark, & Schuler, 2021, forthcoming)

Modeling syntactic acquisition with unsupervised PCFG induction (Jin, Oh, & Schuler, 2021)

Conclusion and future directions

Modeling sentence processing with left-corner parsing

Oh, Clark, and Schuler (2021). Surprisal estimators for human reading times need character models. In *Proc. ACL*.
Oh, Clark, and Schuler (forthcoming). Comparison of structural parsers and neural language models as surprisal estimators. In *Frontiers in AI*.

Expectation-based theories of sentence processing

Processing difficulty is determined by *predictability* in context (Hale, 2001; Levy, 2008)

Predictability can be quantified through information-theoretic *surprisal* (놀라움; Shannon, 1948)

Strong correlation with (human) behavioral and neural measures of processing difficulty
(Demberg & Keller, 2008; Roark et al., 2009; Shain et al., 2020; Smith & Levy, 2013, inter alia)

Expectation-based theories of sentence processing

Surprisal (놀라움)

$$\mathrm{S}(w_t) \stackrel{\mathrm{def}}{=} -\log_2 \mathrm{P}(w_t \mid w_1, w_2, \ldots, w_{t-1})$$

- Can be calculated from any probability model over words
- Open question how to best estimate the language comprehender's probability model

Language models (언어 모델; Goodkind & Bicknell, 2018; Smith & Levy, 2013; Wilcox et al., 2020)

- Trained to predict the next word

Incremental parsers (점진적 파서; Hale et al., 2018; Jin & Schuler, 2020; van Schijndel et al., 2013)

- Trained to predict the next word and (usually syntactic) structure
- Maintains *multiple hypotheses* about structure in *parallel*

In this work

Incremental left-corner parser trained to predict common linguistic abstractions

- Syntactic tree structure with rich node labels (Oh & Schuler, 2021)
- Morphological rules for observed word

Evaluation of parser and LM surprisal on measures of processing difficulty

- Self-paced reading times (Futrell et al., 2021)
- Eye-gaze durations (Kennedy et al., 2003)
- fMRI blood oxygenation level-dependent signals (Shain et al., 2020)

Model description

Left-corner parsing

$$\mathsf{P}(w_t\ q_t \mid q_{t-1}) \;=\; \sum_{\ell_t, g_t} \mathsf{P}(\ell_t \mid q_{t-1}) \cdot \mathsf{P}(w_t \mid q_{t-1}\ \ell_t) \cdot \mathsf{P}(g_t \mid q_{t-1}\ \ell_t\ w_t) \cdot \mathsf{P}(q_t \mid q_{t-1}\ \ell_t\ w_t\ g_t)$$

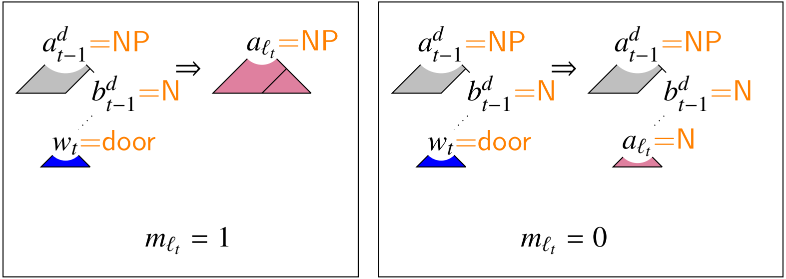
- w_t: Observed word
- q_t: Hidden states representing partial tree structures
- ℓ_t: Lexical decision
- g_t: Grammatical decision

Defines a fixed number of decisions at every word

Model description

Left-corner parsing

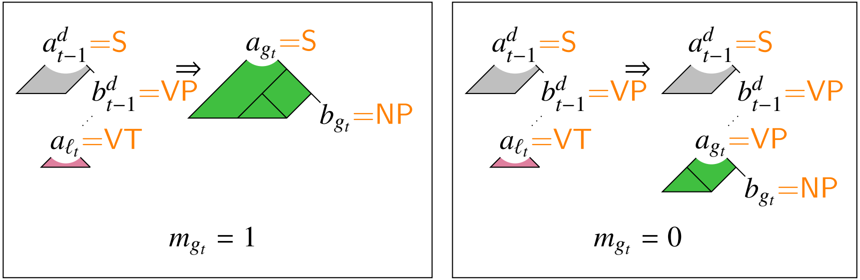
$$\mathsf{P}(w_t\ q_t \mid q_{t-1}) = \sum_{\ell_t, g_t} \mathsf{P}(\ell_t \mid q_{t-1}) \cdot \mathsf{P}(w_t \mid q_{t-1}\ \ell_t) \cdot \mathsf{P}(g_t \mid q_{t-1}\ \ell_t\ w_t) \cdot \mathsf{P}(q_t \mid q_{t-1}\ \ell_t\ w_t\ g_t)$$



Model description

Left-corner parsing

$$\mathsf{P}(w_t\ q_t \mid q_{t-1}) = \sum_{\ell_t, g_t} \mathsf{P}(\ell_t \mid q_{t-1}) \cdot \mathsf{P}(w_t \mid q_{t-1}\ \ell_t) \cdot \color{blue}{\mathsf{P}(g_t \mid q_{t-1}\ \ell_t\ w_t)} \cdot \mathsf{P}(q_t \mid q_{t-1}\ \ell_t\ w_t\ g_t)$$



Model description

Left-corner parsing

$$\mathsf{P}(w_t\ q_t \mid q_{t-1}) = \sum_{\ell_t, g_t} \mathsf{P}(\ell_t \mid q_{t-1}) \cdot \mathsf{P}(w_t \mid q_{t-1}\ \ell_t) \cdot \mathsf{P}(g_t \mid q_{t-1}\ \ell_t\ w_t) \cdot \mathsf{P}(q_t \mid q_{t-1}\ \ell_t\ w_t\ g_t)$$

Character-based word model

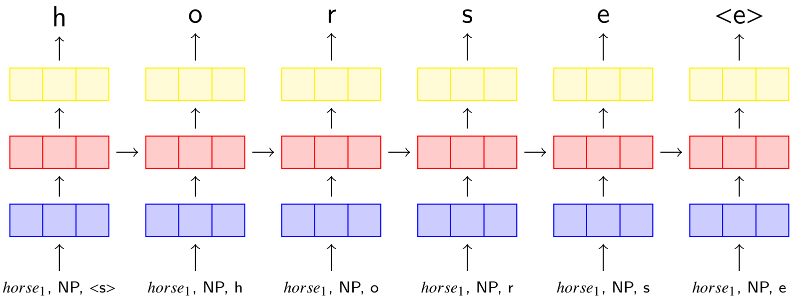
$$\mathsf{P}(w_t \mid q_{t-1}\ \ell_t) = \sum_{x_t, r_t} \mathsf{P}(x_t \mid q_{t-1}\ \ell_t) \cdot \mathsf{P}(r_t \mid q_{t-1}\ \ell_t\ x_t) \cdot \mathsf{P}(w_t \mid q_{t-1}\ \ell_t\ x_t\ r_t)$$

To a lemma x_t, apply a morphological rule r_t for word w_t (to *horse* apply $*\!\rightarrow\!*$s for *horses*)

Model description

Character-based word model

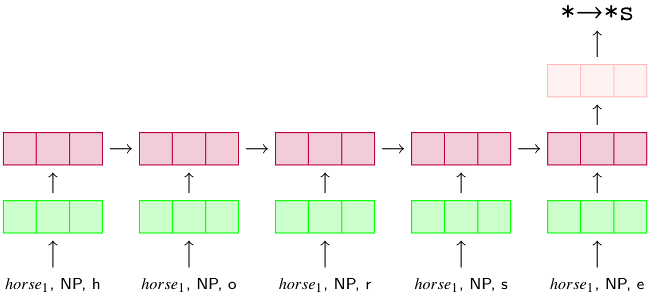
$$\mathrm{P}(w_t \mid q_{t-1}\ \ell_t) = \sum_{x_t, r_t} \mathrm{P}(x_t \mid q_{t-1}\ \ell_t) \cdot \mathrm{P}(r_t \mid q_{t-1}\ \ell_t\ x_t) \cdot \mathrm{P}(w_t \mid q_{t-1}\ \ell_t\ x_t\ r_t)$$



Model description

Character-based word model

$$\mathsf{P}(w_t \mid q_{t-1}\ \ell_t) \ = \ \sum_{x_t, r_t} \mathsf{P}(x_t \mid q_{t-1}\ \ell_t) \ \cdot \ \color{blue}{\mathsf{P}(r_t \mid q_{t-1}\ \ell_t\ x_t)} \ \cdot \ \mathsf{P}(w_t \mid q_{t-1}\ \ell_t\ x_t\ r_t)$$



Surprisal estimation

Parser trained on WSJ02-21 (Marcus et al., 1993)

Surprisal estimated using beam search (빔 탐색)

- Full model (*Structural*)
- Baseline 1: No syntactic category labels for ℓ_t, g_t (*-cat*)
- Baseline 2: Relative frequency estimation for w_t (*-morph*)

Evaluation

Evaluation on three datasets collected during naturalistic language processing

- Natural Stories self-paced reading (Futrell et al., 2021)
- Dundee eye-tracking (Kennedy et al., 2003)
- Natural Stories fMRI (Shain et al., 2020)

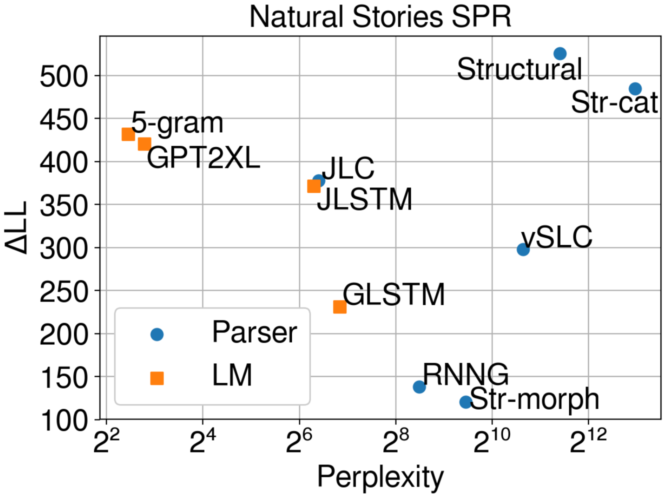
Evaluation metrics (Goodkind & Bicknell, 2018; Hao et al., 2020; Wilcox et al., 2020)

- Perplexity (혼란도): How well does model X predict the next word? ($\downarrow$)
- Δlog-likelihood (Δ 로그우도): How well does surprisal from model X predict the data? ($\uparrow$)

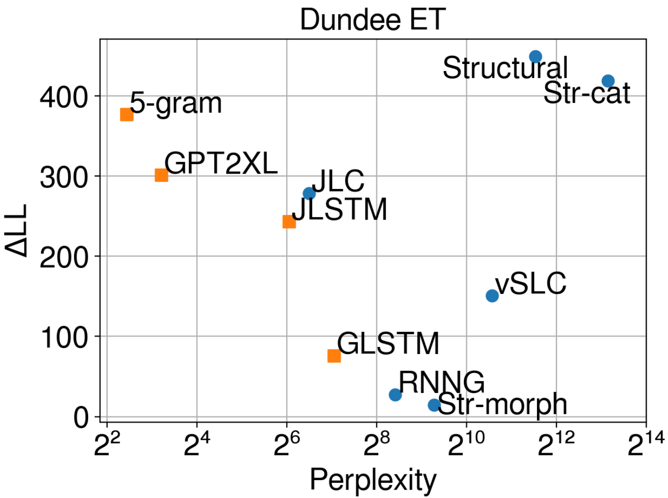
Comparison against surprisal estimates from various models

- LMs: 5-gram (Heafield et al., 2013), GLSTM (Gulordava et al., 2018), JLSTM (Jozefowicz et al., 2016), GPT2XL (Radford et al., 2019)
- Parsers: RNNG (Hale et al., 2018), vSLC (van Schijndel et al., 2013), JLC (Jin & Schuler, 2020)

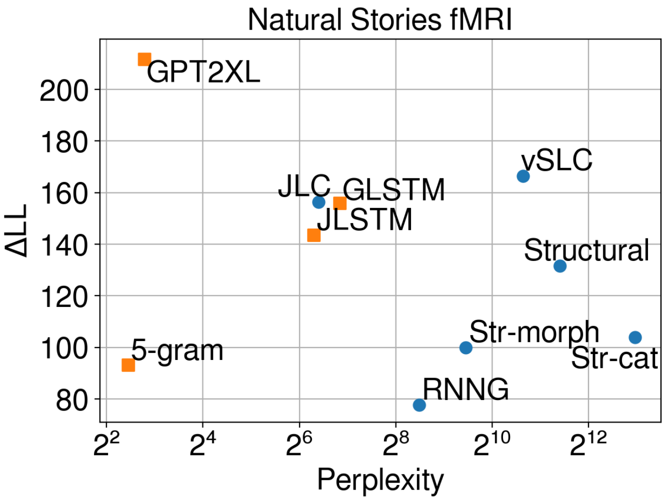
Results (self-paced reading)



Results (eye-tracking)



Results (fMRI)



Summary

Incremental left-corner parser with common linguistic abstractions

Surprisal estimates show better fits to human response data

- Better than large-scale neural LMs on SPR and ET data

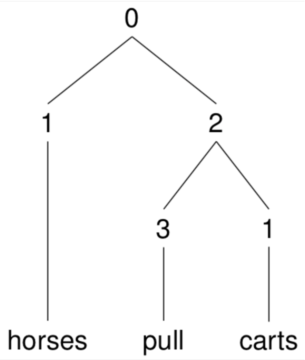
New nuance to the relationship between perplexity and predictive power (Goodkind & Bicknell, 2018; Wilcox et al., 2020)

Modeling syntactic acquisition with unsupervised PCFG induction

Jin, Oh, and Schuler (2021). Character-based PCFG induction for modeling the syntactic acquisition of morphologically rich languages. In *Findings of EMNLP*.

Unsupervised PCFG induction

horses pull carts $\longrightarrow$



Unsupervised PCFG induction

Nonterminal expansion probabilities (비단말 확장):

$P(0 \rightarrow 1\ 2)$

$P(2 \rightarrow 3\ 1)$

...

Terminal expansion probabilities (단말 확장):

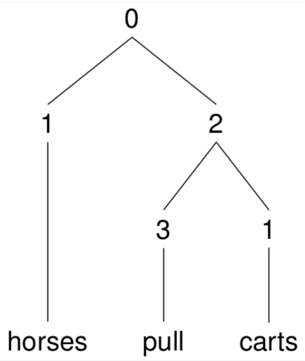
$P(1 \rightarrow \text{horses})$

$P(3 \rightarrow \text{pull})$

$P(1 \rightarrow \text{carts})$

...

$\rightarrow$



Unsupervised PCFG induction

Shows the extent to which grammars can be learned from distributional data alone

Recent neural approaches fairly successful (Kim et al., 2019; Yang et al., 2021; Zhu et al., 2020)

However, word-based PCFGs cannot inspect word affixes

Terminal expansion probabilities:

P(1 $\rightarrow$ horses)

P(3 $\rightarrow$ pull)

P(1 $\rightarrow$ carts)

Unsupervised PCFG induction

Child language learners are sensitive to functional affixes (Dye et al., 2019; Haryu & Kajikawa, 2016; Mintz, 2013)

Word-based models are less appropriate for morphologically rich languages

This work presents

- A character-based model for neural PCFG induction
- Experiments on child-directed speech corpora

Model description

Objective function: marginal probability of sentence σ

$$\mathsf{P}(\sigma) = \sum_{\tau \text{ for } \sigma} \prod_{\eta \in \tau \text{ s.t. } c_\eta \to c_{\eta 1}\ c_{\eta 2}} \mathsf{P}(c_\eta \to c_{\eta 1}\ c_{\eta 2}) \cdot \prod_{\eta \in \tau \text{ s.t. } c_\eta \to w_\eta} \mathsf{P}(c_\eta \to w_\eta)$$

"Split" model: nonterminal or terminal expansion?

$$\mathsf{P}(\mathsf{Term} \mid c_\eta) = \underset{\{0,1\}}{\mathsf{SoftMax}}(\mathsf{ResNet}_{\mathsf{split}}(\mathbf{v}_{\mathbf{c}_\eta}))$$

Model description

Objective function: marginal probability of sentence σ

$$\mathsf{P}(\sigma) = \sum_{\tau \text{ for } \sigma} \prod_{\eta \in \tau \text{ s.t. } c_\eta \to c_{\eta 1}\ c_{\eta 2}} \mathsf{P}(c_\eta \to c_{\eta 1}\ c_{\eta 2}) \cdot \prod_{\eta \in \tau \text{ s.t. } c_\eta \to w_\eta} \mathsf{P}(c_\eta \to w_\eta)$$

Nonterminal expansion probabilities

$$\mathsf{P}(c_\eta \to c_{\eta 1}\ c_{\eta 2}) = \mathsf{P}(\mathsf{Term}{=}0 \mid c_\eta) \cdot \underset{c_{\eta 1}, c_{\eta 2}}{\mathsf{SoftMax}}(\mathbf{W}_{\mathsf{nont}}\, \mathbf{v}_{c_\eta})$$

Model description

Objective function: marginal probability of sentence σ

$$\mathsf{P}(\sigma) = \sum_{\tau \text{ for } \sigma} \prod_{\eta \in \tau \text{ s.t. } c_\eta \to c_{\eta 1}\ c_{\eta 2}} \mathsf{P}(c_\eta \to c_{\eta 1}\ c_{\eta 2}) \cdot \prod_{\eta \in \tau \text{ s.t. } c_\eta \to w_\eta} \mathsf{P}(c_\eta \to w_\eta)$$

Character-based terminal expansion probabilities (*NeuralChar*)

$$\mathsf{P}(c_\eta \to w_\eta) = \mathsf{P}(\text{Term}{=}1 \mid c_\eta) \cdot \prod_{l_i \in \{l_1, \ldots, l_n\}} \mathsf{P}(l_i \mid c_\eta, l_1, \ldots, l_{i-1})$$

Model description

Objective function: marginal probability of sentence σ

$$\mathsf{P}(\sigma) = \sum_{\tau \text{ for } \sigma} \prod_{\eta \in \tau \text{ s.t. } c_\eta \to c_{\eta 1}\ c_{\eta 2}} \mathsf{P}(c_\eta \to c_{\eta 1}\ c_{\eta 2}) \cdot \prod_{\eta \in \tau \text{ s.t. } c_\eta \to w_\eta} \mathsf{P}(c_\eta \to w_\eta)$$

Word-based terminal expansion probabilities (*NeuralWord*)

$$\mathsf{P}(c_\eta \to w_\eta) = \mathsf{P}(\mathrm{Term}{=}1 \mid c_\eta) \cdot \underset{w_\eta}{\mathsf{SoftMax}}(\mathsf{ResNet}_{\mathsf{term}}(\mathbf{v}_{c_\eta}))$$

Evaluation

NeuralChar and *NeuralWord* trained and evaluated on transcriptions of child-directed speech from CHILDES (MacWhinney, 2000)

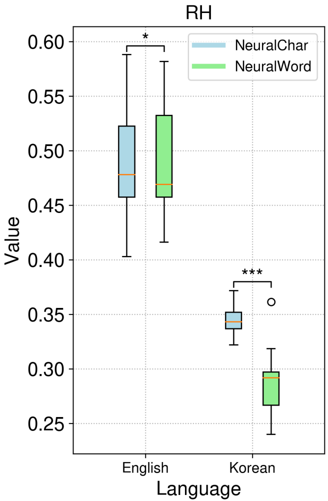
- English (Brown, 1973): Eve (1;6-2;3)
- Korean (Ryu et al., 2015): Jong (1;3-3;5)
- Chinese (Deng et al., 2018): Tong (1;0-4;5)
- German (Behrens, 2006): Leo (1;11-4;11)

Evaluation metric: Recall-Homogeneity (Jin, Schwartz, et al., 2021)

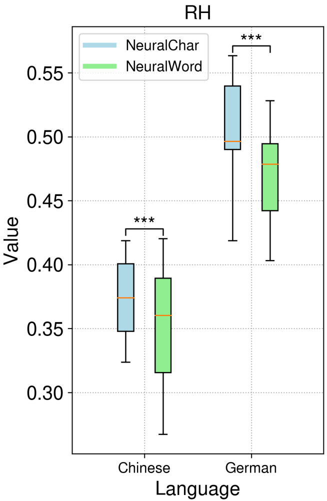
- Recall (재현율): How well does grammar X recall attested constituents? (↑)
- Homogeneity (순도): How homogeneous are syntactic categories of grammar X? (↑)

Results from 10 runs using 90 categories

Results



RH
NeuralChar
NeuralWord
*
***
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
Value
English
Korean
Language



RH
NeuralChar
NeuralWord
***
***
0.55
0.50
0.45
0.40
0.35
0.30
Value
Chinese
German
Language

Induced preterminal categories

Induced category	Count	Attested category (relative frequency)	Examples
NC-63	100	sf (1.0)	.
NC-29	73	npd+jxt (0.23), nq (0.12), ncn (0.12), npd+jcs (0.1), npd (0.1), nq+jcs (0.07), ncn+jcs (0.05)	이거는, 종현이, 이거, 이게, 아빠, 종현아, 종현이가, 이건
NC-62	48	sf (1.0)	?
NC-38	25	px+ef (0.32), pvg+ef (0.2), paa+ef (0.2), pvg+ep+ef (0.16)	와, 있어, 먹어, 갔었어, 졌다, 졌네, 했었어, 놀구요
NC-16	21	pvg+ecx (0.67), pvg+ecs (0.14), paa+ecc (0.1), paa+ef (0.1)	가져, 타러, 보고, 많아요, 알고, 길고, 작아요
NC-2	20	ncn (0.55), ncn+jcj (0.15), ncn+jcs (0.1), pad+ef (0.05), mag (0.05), ncn+jxt (0.05), pvd+ecs (0.05)	엄마, 엄마랑, 엄마가, 그래, 그냥, 엄마는, 그러고
NC-6	20	ii (1.0)	아이구, 아우, 아이고, 아휴, 오, 오오
NC-7	20	pad+ef (1.0)	그렇지, 그래, 그지, 그지요
NW-55	61	sf (1.0)	.
NW-32	51	ii (0.45), pad+ef (0.2), ncn (0.12), mag (0.08), maj (0.06)	그렇지, 어, 짠, 또, 아빠, 자, 엄마, 여기
NW-54	50	sf (1.0)	?
NW-0	46	ncn (0.35), npd+jxt (0.07)	이거는, 이게, 여기, 이, 물, 책, 엄마, 꽃
NW-14	39	sf (1.0)	.
NW-10	34	ncn+jcs (0.24), mag (0.15), ncn (0.06), pvg+ecs (0.06), ncn+jxc (0.06), nq (0.06), paa+ecs (0.06)	많이, 책도, 목이, 꽃이, 가렸네, 백일, 전신, 살이
NW-44	34	paa+ef (0.18), pvg+ef (0.15), ncn+jp+ef (0.09), pvg+ep+ef (0.06), mag (0.06), pvg+etm (0.06), pvg+ef+jxf (0.06), paa+ef+jxf (0.06)	적어요, 아빠가, 때야, 졌다, 졌네, 나와, 그냥, 목욕했어, 보네
NW-29	30	mag (0.2), ncn+jcs (0.1), ncn (0.1), paa+etm (0.1), npp (0.07), pvg+ecx (0.07), ncn+jxt (0.07)	종현이, 너, 다, 작은, 구두는, 진짜, 살, 디게

Summary

A neural model for unsupervised PCFG induction

- Allows clean manipulation of terminal expansion model

Subword information leads to more accurate grammars on child-directed speech

- Bigger impact on morphologically richer languages

Further support for a distributional model of syntactic acquisition

Conclusion and future directions

Conclusion

Parser results show linguistic abstractions are important for capturing humanlike processing difficulty

Inducer results show subword information is important for grammar induction, especially for morphologically rich languages

Computational approaches can be used to model human sentence processing and syntactic acquisition

Future directions

Investigating the contribution of discourse-level information in sentence processing
(e.g. coreference; Jaffe, Oh, & Schuler, 2021)

Modeling language acquisition with more realistic input (e.g. acoustic signals; Shain & Elsner, 2020)

Connecting NLP/ML techniques to psycholinguistic research questions

Thank you for listening!

Parser code: https://github.com/byungdoh/acl21_semproc
Inducer code: https://github.com/lifengjin/charInduction
Regression code: https://github.com/modelblocks/modelblocks-release

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