Toward automatic content analysis of L2 English learners' sentences

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November 3, 2020

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- trains NS model to evaluate non-native speaker (NNS) responses

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- developed & implemented meaning-focused annotation scheme;
- established feature weights for scoring & ranking NNS (benchmark);

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		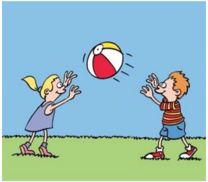
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		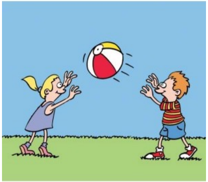
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- 499 participants: 358 NS (crowdsourced), 141 NNS (ESL students)

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		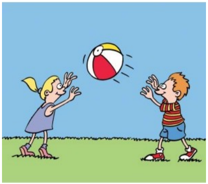
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- 499 participants: 358 NS (crowdsourced), 141 NNS (ESL students)
- 30 items: Roughly 300 NS responses & 140 NNS responses per item

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Solution? Ask NS for **two** different responses.

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- **Interpretability**: evokes clear mental image
- **Verifiability**: info is supported by image

Feature annotation

What is the boy doing?	C	A	G	I	V
He is eating food.	0	1	1	1	1
he eating pizza.	1	1	0	1	1
The boy is smiling pizza.	0	1	0	0	0
He may get fat eating.	0	0	1	1	0

Table: Annotated for five features: Core event (C), Answerhood (A), Grammaticality (G), Interpretability (I) and Verifiability (V).

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Set	A1Yes	Chance	Observed	Kappa
Core Event	0.733	0.601	0.923	0.808
Answerhood	0.834	0.721	0.982	0.936
Grammaticality	0.861	0.768	0.960	0.827
Interpretability	0.818	0.682	0.919	0.744
Verifiability	0.845	0.719	0.968	0.884

Feature reliability

Inter-rater reliability for two annotators and 10% of the dataset: *yes* annotations for Annotator 1 (note skewedness), expected chance agreement (*Chance*), actual observed agreement (*Observed*) and Cohen's kappa (*Kappa*)

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Intransitive	0.863	0.758	0.978	0.910
Transitive	0.780	0.653	0.949	0.853
Ditransitive	0.812	0.678	0.924	0.764

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What is the boy doing?	Pref?	C	A	G	I	V
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the boy is eating pizza	**yes**	**1**	**1**	**1**	**1**	**1**
The child is about to eat pizza.	**yes**	**1**	**0**	**1**	**1**	**1**
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Totals preferred responses		2	2	3	3	3
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Feature weight		.333	.167	.167	.167	.167

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*Real feature weight		.365	.093	.055	.224	.263

Preference reliability (feature weights)

Chance Agree	Observed Agree	Kappa
0.621	0.883 (265/300)	0.692

Table: Preference task agreement scores for two annotators on a sample of 300 response pairs; expected chance agreement, observed agreement and Cohen's Kappa.

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What is the boy doing?	C	A	G	I	V	S_{wa}	R_{wa}
The boy is eating.	0	1	1	1	1	0.635	4
A baby is eating pizza	0	0	1	1	0	0.279	5
The boy enjoys his pizza.	1	0	1	1	1	0.907	2
the boy is eating pizza	1	1	1	1	1	1.0	1
The kid is eats pizza	1	0	0	1	1	0.852	3

Analyzing NNS responses

At this point, my goal is a system that scores and ranks NNS responses via comparison with the crowdsourced NS responses. The system produced ranking should correlate highly with the R_{wa}.

If particular system configuration settings correlate highly with item features (intransitive / transitive / ditransitive; response complexity), I can optimize the system for new items.

Analyzing NNS responses

The system works like this; for each item:

Generate a NS model:

1. dependency parse the collection of NS responses;
2. get tf-idf score for each unique dependency (via a large balanced corpus).

Score each NNS response:

1. As above: dependency parse, tf-idf;
2. Compare NS vs NNS tf-idf vectors: 1 - cosine = response score.

Finally, the NNS responses are ranked by score, and the Spearman rank correlation between R_{wa} and the system is taken as the system configuration score for the item.

By selecting different parameter settings in this approach, I arrive at 12 different system configurations. Each configuration scores and ranks all NNS responses.

System configurations

Consider this simplified set of 2 parameters x 2 settings = 4 configurations.

- **Dependency format**:
  - **labeled**: e.g., nsubj(eat,boy); nobj(eat,pizza)
  - **unlabeled**: e.g., ⟨null⟩(eat,boy); ⟨null⟩(eat,pizza)
- **NS response model**: Note: Each NS participant gave *two* responses per PDT item
  - **first**: Model contains only the first response from NS
  - **mixed**: Model is half first reponses and half second responses

dep\model	first	mixed
labeled	lab_first	lab_mixed
unlabeled	unlab_first	unlab_mixed

System configurations

- Score & rank NNS responses using different configurations;
- Compare with R_{wa} to get a Spearman correlation.

NNS	S_{wa}	R_{wa}	S_{lf}	R_{lf}	S_{uf}	R_{uf}
p1	0.63	4	0.53	4	0.11	5
p2	0.27	5	0.13	5	0.15	4
p3	0.90	2	0.91	1	0.68	1
p4	1.0	1	0.80	2	0.41	2
p5	0.85	3	0.77	3	0.20	3
Spearman ρ			.899		.799	
Spearman p-val			.037		.104	

- *lf* is *labeled_first*; *uf* is *unlabeled_first*:
- *labeled* for labeled dependencies (vs. *unlabeled*)
- *first* for models containing only the first response from NS (vs a *mix* of first and second responses)

Finding trends

From the full set of 360 Spearman correlation scores, I used various subsets of scores to generate hierarchical clusters of the 30 items. I've found some clustering according to verb type (intransitive, transitive or ditransitive), but this trend is not very strong.

I'm currently exploring features other than verb type to see if they correlate with Spearman and can thus help predict optimal system configurations for new items. These features relate to item complexity: type-to-token ratios for the collection of NS responses; mean/median leave-one-out system scores for the NS collection.

Future directions

Other predictive features: image complexity (compression; entropy)

Feedback: Responses scoring below a threshold should be "recast" as the most similar NS response (with $S_{wa} = 1$).
Augment this with SBERT but rely on my system to find appropriate feedback.

For some contexts (e.g., tutoring vs testing), an oracle ranking by the *core event* feature alone may be preferable. Because the feature is binary, Spearman would not be appropriate, so average precision or T-test scores could be used to optimize configurations.

My NNS participants were $>$90% L1 Chinese. I'd love to have an equivalent dataset for another L1 for comparison and to attempt L1-specific optimization.

Generalizing

In a globalized world, we need to be able to analyze speech and text from NNS of English (and other languages). In high stakes contexts, processing should be adaptable, able to abstract from surface form to meaning, and maintain a degree of transparency and explainability.

References

Claudia Leacock, Martin Chodorow, Michael Gamon, and Joel Tetreault. 2014. *Automated Grammatical Error Detection for Language Learners*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, second edition.