Semantic Analysis of Image-Based Learner Sentences

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

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RQ3. What kinds of existing NLP tools and language resources can be integrated to form a content analysis system for open response language learning tasks?

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RQ6. What is the annotation scheme for this task and can the system perform within the range of human performance? Relatedly, what does it mean for a response to be *appropriate* and how can this be captured with annotation?

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The artist is drawing a pretty women. (Ch)
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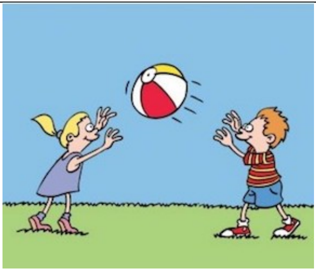
  - MAP *acceptable* responses: ≈51%
- Process is more robust & generalizable;
- Dataset (especially NS models) and annotation are weak;

Main study: Data collection

PDT with very simple images only:

	
Original image	Simplified PDT image

Intended to focus participants' attention on the main action

Main study: Data collection

Two PDT prompt versions:

Targeted	**Untargeted**
	
*What is **the baby** doing?*	*What is happening?*

Intended for exploring the specificity needed for my approach

Main study: Data collection

The pilot study *rake* problem:

- For one PDT item, 100% of NS used the verb *rake*;
  - NNS responses without *rake* are penalized;

NNS Responses
The gardener is *cleaning* the street.
a man *removing* the tree leafs.
The man is *sweeping* the floor.
A man is *gathering* lots of leafs.

- I address this by asking NSs for two non-identical responses.

Main study: Data collection

3 verb types:

10 **intransitive** items	10 **transitive** items	10 **ditransitive** items
		
What is the girl doing?	What is the boy doing?	What is the girl doing?

Intended for exploring whether my approach can generalize to a broader range of sentence types

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  - 29 `familiar`, unpaid colleagues;

	Response Counts		
Group	First	Second	Total
NNS	4290	0	4290
NS (all)	4634	4609	9243
`Familiar`	642	641	1283
`Crowdsrc`	3992	3968	7960
Total	8924	4609	**13,533**

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- Answerhood: Does response directly answer prompt?
- Grammaticality: Is response free from grammar problems?
- Interpretability: Does response evoke a clear mental image?

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- **2**: $+$A, $+$NL $>$ **1**: $+$A, $-$NL $>$ **0**: $-$A, $-$NL
- Not operationalizable: e.g., response is accurate w.r.t. prompt but adds unverifiable details; is this still *accurate*?
- Not *reliable*, not *valid*;

Several iterations later, 5 binary features:

- CORE EVENT: Does response capture main action?
- ANSWERHOOD: Does response directly answer prompt?
- GRAMMATICALITY: Is response free from grammar problems?
- INTERPRETABILITY: Does response evoke a clear mental image?
- VERIFIABILITY:

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Annotation features

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).

Annotation features

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Inter-rater reliability for two annotators and 10% of the dataset:

Annotation features

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*)

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
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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Problem: My system provides a similarity score between 0 and 1.
How can I evaluate system performance?

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I need **benchmark response rankings** for the NNS test set.

Solution: Determine feature weights and apply to annotations to obtain benchmark holistic scores and then rankings.

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Raters perform holistic preference test (blind to annotations)

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What is the boy doing?	Pref?	Core	Ansr	Gram	Intrp	Verif
He is eating food.	**yes**	**0**	**1**	**1**	**1**	**1**
He may get fat eating.	no	0	0	1	1	0

Weighting features

Raters perform holistic preference test (blind to annotations)

What is the boy doing?	Pref?	Core	Ansr	Gram	Intrp	Verif
He is eating food.	**yes**	**0**	**1**	**1**	**1**	**1**
He may get fat eating.	no	0	0	1	1	0
He is hungry.	no	0	0	1	0	1
the boy is eating pizza	**yes**	**1**	**1**	**1**	**1**	**1**

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He may get fat eating.	no	0	0	1	1	0
He is hungry.	no	0	0	1	0	1
the boy is eating pizza	**yes**	**1**	**1**	**1**	**1**	**1**
The child is about to eat pizza.	**yes**	**1**	**0**	**1**	**1**	**1**
he eating.	no	0	1	0	1	1

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He is hungry.	no	0	0	1	0	1
the boy is eating pizza	**yes**	**1**	**1**	**1**	**1**	**1**
The child is about to eat pizza.	**yes**	**1**	**0**	**1**	**1**	**1**
he eating.	no	0	1	0	1	1
Totals preferred responses		2	2	3	3	3
Totals dispreferred responses		0	1	2	2	2
Net preferred (pref - dispref)		2	1	1	1	1
Feature weight		.333	.167	.167	.167	.167

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the boy is eating pizza	**yes**	**1**	**1**	**1**	**1**	**1**
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Feature weight		.333	.167	.167	.167	.167
*Real feature weight		.365	.093	.055	.224	.263

Weighting features

Preferences are reliable:

Agreement for two annotators on a sample of 300 response pairs:

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

Benchmark rankings

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What is happening?	C	A	G	I	V	WAS	WAR
The boy is eating pizza	0.365	0.093	0.055	0.224	0.263	1.000	1
Child is eating pizza	0.365	0.093	0.000	0.224	0.263	0.945	2
Tommy is eating pizza	0.365	0.093	0.055	0.224	0.000	0.737	3
The boy's eating his favorite food	0.000	0.093	0.055	0.000	0.000	0.513	4
Pizza is this boy's favorite food	0.000	0.000	0.055	0.000	0.000	0.055	5

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The boy's eating his favorite food	0.000	0.093	0.055	0.000	0.000	0.513	4
Pizza is this boy's favorite food	0.000	0.000	0.055	0.000	0.000	0.055	5

- Use WAR as benchmark;
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Pizza is this boy's favorite food	0.000	0.000	0.055	0.000	0.000	0.055	5

- Use WAR as benchmark;
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  - Holistic: Get Spearman for system ranking vs. WAR;

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  - Term representation parameter (`ldh`, `xdh`, `xdx`) does not apply.

System configuration

Optimizing my system means searching for the settings that yield the best performance; i.e., system output best approximates benchmark (WAR).

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  - `targeted`: *What is <the subject> doing?*
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  - `primary`: NS model contains only 1st responses;
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  - `primary`: NS model contains only 1st responses;
  - `mixed`: NS model: 1st & 2nd responses (50-50);
- **Term Representation**:
  - `ldh`: label-dependent-head; i.e., labeled dependencies;
  - `xdh`: dependent-head; i.e., unlabeled dependencies;
  - `xdx`: dependent only; cf. *bag of words*;

System configuration

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All parameters or variables and their settings:

Transitivity	**Targeting**	**Familiarity**	**Primacy**	**Term Rep.**
`intransitive`	`targeted`	`familar`	`primary`	`ldh`
`transitive`	`untargeted`	`crowdsourced`	`mixed`	`xdh`
`ditransitive`				`xdx`

A **system configuration** combines one setting from each column.

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

Sampling data

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NNS test sets:

- All experiments rank the same randomly sampled NNS test sets;
- 70 responses per PDT item (max available for NNS data);
  - 70 `targeted`, 70 `untargeted`

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  - 70 `targeted`, 70 `untargeted`

NS models:

- 14-response models (max available for `familiar` data);
  - I.e., I compare 14-response `familiar` models and 14-response `crowdsourced` models;
- 50-response models (max available for `crowdsourced` data);

Sampling data: Complexity

Standardized type-to-token ratio (STTR) for the response samples. Tokens here are *dependencies*.

	n14		n50	n70
	Fam	Crd	Crd	NNS
Intrans	0.55	0.52	0.53	0.39
Trans	0.56	0.58	0.58	0.51
Ditrans	0.59	0.64	0.63	0.60
Target	0.54	0.53	0.54	0.48
Untarg	0.61	0.63	0.62	0.52
primary	N/A	0.51	0.52	0.50
mixed	0.57	0.65	0.64	N/A
xdx	0.36	0.42	0.42	0.36
xdh	0.65	0.66	0.66	0.57
ldh	0.66	0.66	0.67	0.57
Total	0.57	0.58	0.58	0.50

Annotation features experiments: Core event MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	***0.85***	0.85	0.85	0.86	0.83	**0.85**	0.85	0.85	0.86	0.83
Tran	***0.73***	0.73	0.72	0.74	0.70	**0.73**	0.73	0.72	0.74	0.70
Ditr	***0.66***	0.66	0.66	0.66	0.63	0.65	0.65	**0.66**	0.66	0.62
Targ	***0.73***	0.73	0.73	0.73	0.70	**0.73**	0.73	0.72	0.73	0.70
Untg	***0.76***	0.76	0.76	0.77	0.74	0.76	0.75	**0.76**	0.77	0.73
Prim	***0.75***	0.75	0.74	0.75	0.72	**0.75**	0.74	0.74	0.75	0.71
Mix	***0.75***	0.74	0.75	0.75	0.72	**0.74**	0.74	0.74	0.75	0.72
Total	***0.75***	0.75	0.74	0.75	0.72	**0.75**	0.74	0.74	0.75	0.72

- In all cases, ldh + 14NS is best;
- xdx becomes more competitive for larger model (50NS);
  - ditransitive, untargeted: responses to these are *least homogenous*—i.e., highest TTRs;
  - In general: ldh TTR > xdh TTR > xdx TTR

Annotation features experiments: CORE EVENT MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	0.85	0.85	***0.86***	0.86	0.83	**0.85**	0.85	0.84	0.86	0.83
Tran	***0.74***	0.73	0.72	0.74	0.70	**0.73**	0.73	0.72	0.74	0.70
Ditr	0.65	0.64	**0.66**	0.66	0.62	0.66	0.65	***0.67***	0.66	0.64
Targ	**0.73**	0.73	0.73	0.73	0.70	***0.73***	0.73	0.73	0.73	0.70
Untg	0.76	0.76	***0.76***	0.77	0.73	**0.76**	0.76	**0.76**	0.77	0.74
Total	0.75	0.74	**0.75**	0.75	0.72	***0.75***	0.74	0.75	0.75	0.72

- Totals: crowdsourced outperforms familiar (slightly);
- crowdsourced works best with ldh;
- familiar works best with xdx;

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- `familiar` 14NS > `crowd` 14NS > `crowd` 50NS;

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Predicting ANSWERHOOD or GRAMMATICALITY is relatively simple; requires only small model and bag-of-words representation.

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- 14NS `crowd` > 50NS `crowd` > 14NS `familiar`;
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- `intransitives` & `ditransitives` work best with `xdx`;

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- `intransitives` & `ditransitives` work best with `xdx`;
- `transitives` work best with `ldh`;
  - Why? `Transitive` responses are relatively homogenous; Annotators relatively strict;

Holistic experiments

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Holistic experiments use one set of 360 Spearman correlations:

targeting (2) $\times$ primacy (2) $\times$ term rep (3) $\times$ items (30) $= 360$.

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Each experiment focuses on one variable, e.g., targeting:

Divide 360 into 180 `targeted` scores and 180 `untargeted` scores; compare mean, median, etc.

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SBERT uses plain text (no term rep), thus only 120 total.

Holistic experiments

Holistic experiments use one set of 360 Spearman correlations:

targeting (2) $\times$ primacy (2) $\times$ term rep (3) $\times$ items (30) $=$ 360.

(`Familiar` vs. `Crowd` handled separately due to sparse data.)

Each experiment focuses on one variable, e.g., targeting:

Divide 360 into 180 `targeted` scores and 180 `untargeted` scores; compare mean, median, etc.

SBERT uses plain text (no term rep), thus only 120 total.

(SBERT always wins over system.)

Holistic experiments: Transitivity

		intrans		trans		ditrans	
		Sys	SBERT	Sys	SBERT	Sys	SBERT
	count	120	40	120	40	120	40
14NS	mean	***0.439***	0.497	0.314	0.563	0.267	0.400
	median	**0.416**	0.479	0.304	0.555	0.276	0.444
50NS	mean	**0.423**	0.516	*0.345*	0.566	*0.278*	0.446
	median	***0.426***	0.517	*0.331*	0.561	*0.286*	0.471

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  - `trans` & `ditrans`: 50NS model is best;

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- System, regardless of model size: `intrans` > `trans` > `ditrans`;
- More complex items (TTR) work best with larger models;
  - `trans` & `ditrans`: 50NS model is best;
  - `intrans`: 14NS gives best median, 50NS gives best mean;

Holistic experiments: Results

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Targeting:

Holistic experiments: Results

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- `targeted` > `untargeted`

Holistic experiments: Results

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Familiarity (14NS models only):

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- System: No discernible difference for `familiar` vs `crowdsourced`

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- `targeted` > `untargeted`
- 50NS models > 14NS models
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Familiarity (14NS models only):

- System: No discernible difference for `familiar` vs `crowdsourced`
- SBERT: `familiar` > `crowdsourced`
  - NNS STTR < `familiar` STTR < `crowdsourced` STTR

Holistic experiments: Results

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Primacy:

Holistic experiments: Results

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- SBERT: `primary` $>$ `mixed`
- System & SBERT: 50NS $>$ 14NS

Holistic experiments: Results

Primacy:

- System: 14NS: `primary` < `mixed` (slight difference)
- System: 50NS: `primary` ≈ `mixed`
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- System & SBERT: 50NS > 14NS
    - System: model size effect is greatest for `primary`

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Term representation:

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Term representation:

- SBERT: 50NS > 14NS
- System: for `ldh` & `xdh`: 50NS > 14NS;

Holistic experiments: Results

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- System: 50NS: `primary` $\approx$ `mixed`
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- SBERT: 50NS $>$ 14NS
- System: for `ldh` & `xdh`: 50NS $>$ 14NS;
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- System: 50NS: `primary` $\approx$ `mixed`
- SBERT: `primary` $>$ `mixed`
- System & SBERT: 50NS $>$ 14NS
  - System: model size effect is greatest for `primary`

Term representation:

- SBERT: 50NS $>$ 14NS
- System: for `ldh` & `xdh`: 50NS $>$ 14NS;
  - Model size effect is greater for `ldh`
- System: for `xdx`: NS14 $>$ NS50 (very slight)

Summary

NTS: one slide

Outlook

NTS: one slide

References

Sampling data: Response length

	n=14		n=50	n=70
	Fam	Crowd	Crowd	NNS
Intrans	5.5	4.9	4.9	4.9
Trans	6.9	6.3	6.2	6.7
Ditrans	7.8	7.2	7.2	8.3
Target	6.5	5.4	5.4	6.3
Untarg	6.9	6.8	6.8	6.9
primary	N/A	5.7	5.8	6.6
mixed	6.7	6.5	6.4	N/A
Total	6.7	6.1	6.1	6.6

Table: Comparing average response length (in words) for the samples used throughout this chapter as NS models and NNS test sets, in total and by parameter setting.