Semantic Analysis of Image-Based Learner Sentences

Levi King
Indiana University

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Background & Motivation

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

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RQ5. Can the accuracy of the system be improved with information from semantic tools (e.g., BERT)?

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RQ4. How do "bag-of-words" and "bag-of-dependencies" approaches compare in terms of performance?

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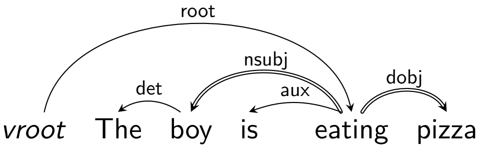
RQ6. What is the annotation scheme for this task and can the system perform within the range of human performance?

System

Step 1: Dependency parse:



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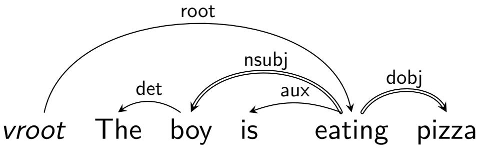

Get dependencies:
root(eating, *vroot*)
det(the, boy)
nsubj(boy, eating)
aux(is, eating)
dobj(pizza, eating)

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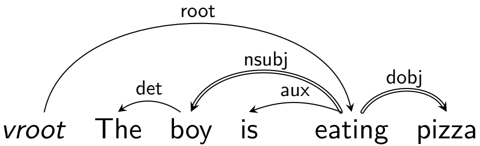

Get dependencies:		**Step 2: Lemmatize:**
root(eating, *vroot*)	$\rightarrow$	root(**eat**, *vroot*)
det(the, boy)	$\rightarrow$	det(the, boy)
nsubj(boy, eating)	$\rightarrow$	nsubj(boy, **eat**)
aux(is, eating)	$\rightarrow$	aux(**be**, **eat**)
dobj(pizza, eating)	$\rightarrow$	dobj(pizza, **eat**)

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NS ∪ NNSs	NS model		NNS 1		NNS 2	
	tf	tf-idf	tf	tf-idf	tf	tf-idf
aux(be,eat)	2	.04	1	.02	1	.02
det(the,boy)	1	.04	-	0	-	0
dobj(food,eat)	-	0	1	.06	-	0
dobj(pizza,eat)	2	.16	-	0	1	.08
nsubj(boy,eat)	1	.08	-	0	-	0
nsubj(he,eat)	1	.04	1	.02	1	.02
root(eat,vroot)	2	.02	1	.01	1	.01

Response scores: cosine(NS model tf-idf, NNS tf-idf)

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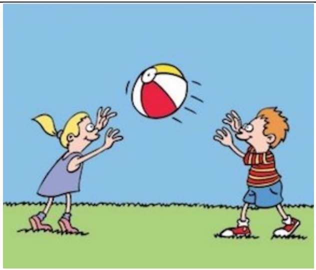
NNS 1: 0.139 NNS 2: 0.886 $\rightarrow$ *NNS 2 is closest to the model.*

Data collection

PDT with very simple images only:

	
Original image	Simplified PDT image

Intended to focus participants' attention on the main action

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

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 range of sentence types

Data collection

The pilot study *rake* problem; 100% of NS used the verb *rake*:

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.

- NNS responses without *rake* are penalized;
- I address this by asking NSs for two non-identical responses.

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    - 7,960 responses;
  - 29 `familiar`, unpaid colleagues;
    - 1,283 responses;

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5 binary features:

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- Interpretability: Does response evoke a clear mental image?
- Verifiability: Is all response info supported by image?

Annotation features

Core event, **A**nswerhood, **G**rammaticality, **I**nterpretability, **V**erifiability

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

Inter-rater reliability (Cohen's kappa): 0.744 (**I**) – 0.936 (**A**)

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

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Preferences are reliable:

Agreement for two annotators on a sample of 300 pairs:

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

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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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- State-of-the-art sentence embedding for semantic textual similarity.
- Replaces dependency parser + lemmatizer + tf-idf cosine pipeline.
- Provides distance between NNS response and NS model.

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- **Term Representation**:
  - `ldh`: label-dependent-head; i.e., labeled dependencies;
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A **system configuration** combines one setting from each.

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- All experiments rank the same randomly sampled NNS test sets;
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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

	n14		n50	n70
	Fam	Crd	Crd	NNS
Intrans	.558	.525	.535	.391
Trans	.569	.580	.581	.517
Ditrans	.598	.640	.637	.606
Target	.545	.535	.545	.481
Untarg	.610	.633	.621	.528
Primary	N/A	.517	.523	.505
Mixed	.576	.652	.645	N/A
xdx	.364	.424	.421	.364
xdh	.658	.661	.660	.572
ldh	.665	.664	.671	.578
Total	.576	.583	.584	.505

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

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Within each parameter block, complexity increases as we move down the rows. E.g.:

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	n14		n50	n70
	Fam	Crd	Crd	NNS
Intrans	.558	.525	.535	.391
Trans	.569	.580	.581	.517
Ditrans	.598	.640	.637	.606
Target	.545	.535	.545	.481
Untarg	.610	.633	.621	.528
Primary	N/A	.517	.523	.505
Mixed	.576	.652	.645	N/A
xdx	.364	.424	.421	.364
xdh	.658	.661	.660	.572
ldh	.665	.664	.671	.578
Total	.576	.583	.584	.505

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

Complexity often correlates with parameter settings in terms of system performance.

Within each parameter block, complexity increases as we move down the rows. E.g.:

Intrans < Trans < Ditrans

Sampling data: Complexity

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Within each parameter block, complexity increases as we move down the rows. E.g.:

`Intrans` < `Trans` < `Ditrans`

In some settings (e.g., `Intrans`), `Crowd` complexity is closer to NNS than is `Familiar`; other settings vice versa (e.g., `Ditrans`).

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 (slightly);
- `xdx` becomes more competitive for larger model (50NS);
  - `ditrans`, `untarg`: *least homogenous*—i.e., highest STTRs;
  - In general: `ldh` STTR > `xdh` STTR > `xdx` STTR

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

- *mixed only (due to sparse familiar data);
- Totals: crowdsourced outperforms familiar (slightly);
- crowdsourced works best with ldh;
- familiar works best with xdx;

Annotation features experiments: MAP Results

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For all 5 features, my system outperforms SBERT.

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- `xdx` $>$ `xdh` $>$ `ldh`;
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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.

Annotation features experiments: MAP Results

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For both INTERPRETABILITY & VERIFIABILITY:

- `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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(SBERT always wins over system.)

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		`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
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Holistic experiments: Results

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- System & SBERT: 50NS $>$ 14NS

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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

Dependency parsing

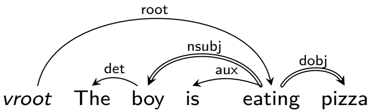

Figure: The dependency parse

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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?

Pilot study: Data

Response (L1)
He is droning his wife pitcher. (Ar)
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Figure: Example item from the pilot study showing responses from native speakers of Arabic (Ar), Chinese (Ch), English (En) and Spanish (Sp).

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- Annotation: *Given the prompt, would the response be acceptable to most English speakers? Acceptable/unacceptable*
  - 1 annotator (me)

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The painter is painting a woman's paint. (Sp)

Figure: Example item from the pilot study showing responses from native speakers of Arabic (Ar), Chinese (Ch), English (En) and Spanish (Sp).

- 10 (transitive) PDT items $\times$ 53 participants $=$ 530 responses;
  - 14 NSs (grad students), 39 NNSs (ESL students);
- Annotation: *Given the prompt, would the response be acceptable to most English speakers? Acceptable/unacceptable*
  - 1 annotator (me)

Pilot study: Processing

First approach: **Rule-based** triple extraction and matching

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  - Custom for my transitive PDT, not generalizable, not robust;
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- Overall accuracy: 58.9%
  - I.e., *Acceptable* covered, *unacceptable* not covered;

Pilot study: Processing

Second approach: **Semantic similarity** scoring

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Dependency parser → lemmatizer → term frequency-inverse document frequency (tf-idf; "term" = lemmatized dependency);

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  - Get *sorted union set* of NS and NNS dependencies;

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  - NS vector: Replace deps with their **NS** tf-idf scores;
  - Response score = *cosine distance* for NNS & NS vectors;

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- Rank by scores & calculate Mean Average Precision (MAP);

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- Process is more robust & generalizable;

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  - NS vector: Replace deps with their **NS** tf-idf scores;
  - Response score = *cosine distance* for NNS & NS vectors;
- Rank by scores & calculate Mean Average Precision (MAP);
  - MAP *acceptable* responses: ≈51%
- Process is more robust & generalizable;
- Dataset (especially NS models) and annotation are weak;

System configuration

System configuration

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: 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.

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- **2**: $+$A, $+$NL $>$ **1**: $+$A, $-$NL $>$ **0**: $-$A, $-$NL

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- Not operationalizable: e.g., response is accurate w.r.t. prompt but adds unverifiable details; is this still *accurate*?
- Not *reliable*, not *valid*;

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- Not operationalizable: e.g., response is accurate w.r.t. prompt but adds unverifiable details; is this still *accurate*?
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This was scrapped and I settled on the 5 binary features.

Annotation features

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

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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

Weighting features

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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What is the boy doing?	Pref?	Core	Ansr	Gram	Intrp	Verif
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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
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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Feature weight		.333	.167	.167	.167	.167
*Real feature weight		.365	.093	.055	.224	.263