Semantic Analysis of Image-Based Learner Sentences

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Background & Motivation

Most intelligent computer-assisted language learning (ICALL) applications (*Rosetta Stone*, *Duolingo*, etc.) rely on outdated, ineffective methods:

- rote memorization & grammatical error detection; menu-based vs. free input;
- *“engineering first”*: no second language acquisition, pedagogy;

SLA research → communicative & task-based learning

How can we bridge this gap?

- My vision: open source app; transparent; pipeline of existing tools;
- teachers create new games/stories by adding visual prompts and crowdsourcing native speaker (NS) responses;
- use NS model to evaluate non-native speaker (NNS) responses

Research Questions

RQ1. Are the picture description task (PDT) responses of L2 English learners sufficiently similar to those of NSs to allow automatic evaluation based on a collection of NS responses?

RQ2. For PDT responses, what are appropriate representations for the purpose of providing meaning-oriented feedback or evaluation?

RQ3. What kinds of NLP tools are appropriate here?

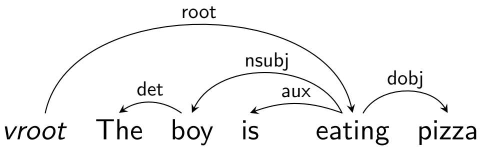
RQ4. How do “bag-of-words” and “bag-of-dependencies” approaches compare in terms of performance?

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

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:



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

System

Step 3: tf-idf (term frequency-inverse document frequency)

NS model: [He is eating pizza. The boy is eating pizza.]

NNS 1: He is eating food. NNS 2: He is eating pizza.

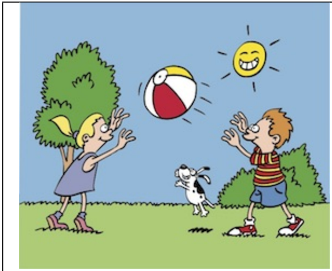
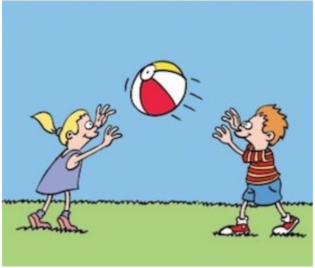
NS ∪ NNSs	NS model		NNS 1		NNS 2	
	tf	tf-idf	tf	tf-idf	tf	tf-idf
aux(be,eat)	2	.04	1	.02	1	.02
det(the,boy)	1	.04	-	0	-	0
dobj(food,eat)	-	0	1	.06	-	0
dobj(pizza,eat)	2	.16	-	0	1	.08
nsubj(boy,eat)	1	.08	-	0	-	0
nsubj(he,eat)	1	.04	1	.02	1	.02
root(eat,vroot)	2	.02	1	.01	1	.01

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

NNS 1: 0.139 NNS 2: 0.886 → *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

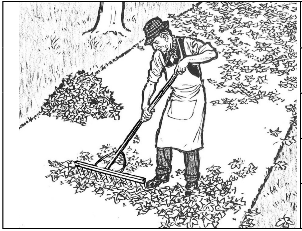
3 verb types:

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.

Main study: Data collection

499 participants, 13,533 responses:

- 141 NNSs (ELIP at IU), 4,290 responses;
  - 125 Mandarin, 4 Korean, 3 Burmese, 2 Hindi; 1 each: Arabic, Indonesian, German, Gujarati, Spanish, Thai, Vietnamese;
- 358 NSs, 9,243 responses:
  - 329 `crowdsourced`, purchased via SurveyMonkey;
    - 7,960 responses;
  - 29 `familiar`, unpaid colleagues;
    - 1,283 responses;

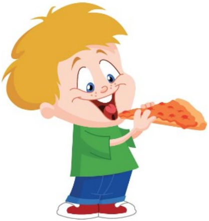
Annotation features

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: 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**)

Evaluating performance

Problem: My system scores are between 0 and 1, but annotation is 5 binary scores. How can I evaluate system performance?

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

Feature-level performance:

- Mean average precision (**MAP**) to see how system rankings predict **individual features**;
    - Compare with? Some *holistic benchmark ranking* MAP;

Holistic performance (response quality):

- **Spearman** rank correlation: Compare system rankings with some *holistic benchmark ranking*;

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

Weighting features

Annotators performed a preference task for pairs of responses.

Feature weights were derived according to how frequently each feature is “yes” among preferred responses.

Core	Answer	Gramm.	Interp.	Verif.
.365	.093	.055	.224	.263

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

Benchmark rankings

1. Apply feature weights for weighted annotation scores (WAS);
2. Rank NNS test set by WAS for weighted annotation ranking (WAR);

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

SBERT for comparison

I also use SBERT for comparing my system's performance.

- 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; rankable.

System configuration

Optimizing means finding the best system settings:

- **Transitivity**: `intransitive`, `transitive`, `ditransitive`;
- **Targeting**: `targeted`, `untargeted`;
- **Familiarity**: `familiar`, `crowdsourced`;
- **Primacy**:
  - `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*;
  - Does not apply to SBERT (operates on plain text);

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

Sampling data

NNS test sets:

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

NS models:

- 14-response models (max available for `familiar` data);
- 50-response models (max available for `crowdsourced` data);

Sampling data: Complexity

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

	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

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`

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: *most complex*—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

For all 5 features, my system outperforms SBERT.

ANSWERHOOD, in *all* cases:

- `xdx` > `xdh` > `ldh`;
- Model size makes no difference;
- `familiar` > `crowdsourced`;

GRAMMATICALITY, in *most* cases:

- `xdx` > `xdh` > `ldh`;
- `familiar` 14NS > `crowd` 14NS > `crowd` 50NS;

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

Annotation features experiments: MAP Results

INTERPRETABILITY:

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

VERIFIABILITY:

- 14NS crowd > 50NS crowd > 14NS familiar;
- Model size effect is most pronounced with untargeted & mixed;
    - Unconstrained settings; larger models have more noise;

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

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

- SBERT, regardless of model size: trans > intrans > ditrans;
- 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 mean, 50NS gives best median;

Holistic experiments: Results

Targeting:

- `targeted` > `untargeted`
- 50NS models > 14NS models
  - Model size effect is most pronounced for `targeted`

Familiarity (14NS models only):

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

Holistic experiments: Results

Primacy:

- System: 14NS: `primary` $<$ `mixed` (slight difference)
- 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

Dependency parsing

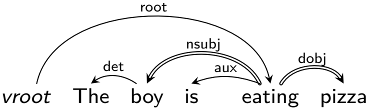


Figure: The dependency parse

Research Questions

RQ1. Are the responses of L2 English learners sufficiently similar to those of NSs to allow automatic evaluation based on a collection of NS responses? In other words, do learners demonstrate significant overlap with native-like usage in a picture description task (PDT) setting?

RQ2. In the constrained communicative environment of a PDT, what are appropriate response and model representations for the purpose of providing meaning-oriented feedback or evaluation? In other words, which linguistic components are crucial and which are superfluous?

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?

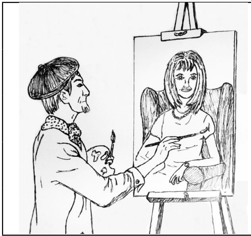
Research Questions

RQ4. How do “bag-of-words” and “bag-of-dependencies” approaches compare in terms of performance? Is a bag-of-words approach alone adequate for our needs?

RQ5. Can the accuracy of the system be improved by the inclusion of semantic information from tools like semantic role labelers, WordNet, or word and sentence embeddings?

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)
The artist is drawing a pretty women. (Ch)
The artist is painting a portrait of a lady. (En)
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 × 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

Dependency parser → lemmatizer → *V(S,O)* extraction rules;

Compare NNS *V(S,O)* & NS *V(S,O)* list → covered / not covered;

- Dependency-based
  - Captures aspects of form and meaning;
  - Subjects, objects, verbs clearly labeled;
- V(S,O) extraction
  - Decision tree based on dependency indexing & labels, POS;
  - Custom for my transitive PDT, not generalizable, not robust;
  - ≈92% accurate, ≈8% extraction errors;
- Overall accuracy: 58.9%
  - I.e., *Acceptable* covered, *unacceptable* not covered;

Pilot study: Processing

Second approach: **Semantic similarity** scoring

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

NNS response score = cosine distance of NS and NNS tf-idf scores;

- tf-idf: Score dependencies according to importance;
- Vectorize & Score
  - Get *sorted union set* of NS and NNS dependencies;
  - NNS vector: Replace deps with their **NNS** tf-idf scores;
  - 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

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.

Annotation features

First iteration: **accuracy (A)** & **native-likeness (NL)**

- **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*;

This was scrapped and I settled on the 5 binary features.

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

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