Semantic Analysis of Image-Based Learner Sentences

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

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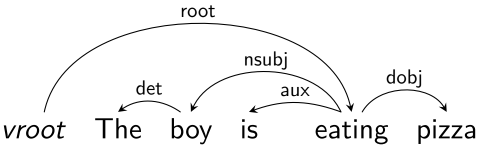
RQ6. What is the annotation scheme for this task and can the system perform within the range of human performance?

System

Step 1: Dependency parse:



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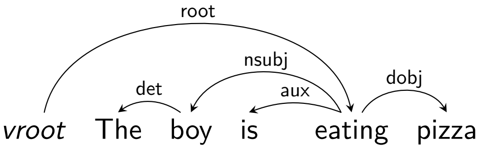

Get dependencies:
root(eating, *vroot*)
det(the, boy)
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aux(is, eating)
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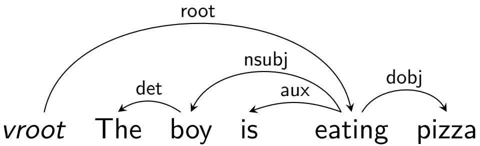

Get dependencies:	**Step 2: Lemmatize:**
root(eating, *vroot*)	→ root(**eat**, *vroot*)
det(the, boy)	→ det(the, boy)
nsubj(boy, eating)	→ nsubj(boy, **eat**)
aux(is, eating)	→ aux(**be**, **eat**)
dobj(pizza, eating)	→ dobj(pizza, **eat**)

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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

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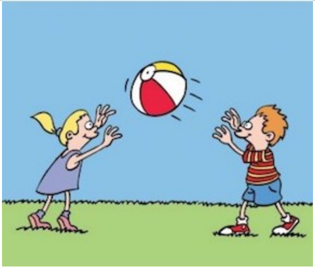
NNS 1: 0.139; NNS 2: 0.886 $\rightarrow$ *NNS 2 is closest to the model.*

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

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5 binary features:

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- 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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- Annotators performed a preference task for pairs of responses.
- Feature weights were derived according to how frequently each feature is “yes” among preferred responses.

Benchmark rankings

Weighted annotation score (WAS); *weighted annotation ranking* (WAR)

What is happening?	C	A	G	I	V	WAS	WAR
The boy is eating pizza	.365	.093	.055	.224	.263	10	1
Child is eating pizza	.365	.093	0	.224	.263	.945	2
Tommy is eating pizza	.365	.093	.055	.224	0	.737	3
The boy's eating his favorite food	0	.093	.055	0	0	.513	4
Pizza is this boy's favorite food	0	0	.055	0	0	.055	5

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Agreement for two annotators on a sample of 300 pairs:

Chance Agree	Observed Agree	Cohen's Kappa
.621	.883 (265/300)	.692

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    - Dependencies *are* suitable.

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

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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

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

`Intrans` < `Trans` < `Ditrans`

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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`).

Predicting features: CORE EVENT MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	***.859***	.856	.854	.865	.835	**.855**	.854	.852	.865	.831
Tran	***.737***	.735	.728	.742	.703	**.736**	.733	.725	.742	.701
Ditr	***.665***	.661	.664	.660	.634	.657	.656	**.661**	.660	.629
Targ	***.739***	.738	.732	.735	.708	**.737**	.735	.729	.735	.704
Untg	***.768***	.763	.765	.777	.740	.762	.759	**.763**	.777	.736
Prim	***.754***	.752	.747	.756	.723	**.750**	.748	.745	.756	.719
Mix	***.753***	.749	.750	.756	.725	**.749**	.746	.746	.756	.721
Total	***.735***	.751	.748	.756	.724	**.750**	.747	.746	.756	.720

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Intr	.859	.859	***.865***	.865	.838	**.857**	.852	.848	.865	.833
Tran	***.740***	.737	.726	.742	.703	**.738**	.735	.728	.742	.702
Ditr	.651	.648	**.660**	.660	.625	.663	.659	***.673***	.660	.641
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Predicting ANSWERHOOD or GRAMMATICALITY is relatively simple; requires only small model and bag-of-words representation.

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Predicting features: MAP Results

Interpretability:

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Verifiability:

Predicting features: MAP Results

INTERPRETABILITY:

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

VERIFIABILITY:

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

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

Predicting quality

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

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(SBERT always wins over system.)

Predicting quality: `Transitivity`

Spearman rank correlations: System vs. WAR (benchmark)

		`intrans`		`trans`		`ditrans`	
		Sys	SBERT	Sys	SBERT	Sys	SBERT
	count	120	40	120	40	120	40
14NS	mean	***.439***	.497	.314	.563	.267	.400
	median	**.416**	.479	.304	.555	.276	.444
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Targeting:

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  - NNS STTR < `familiar` STTR < `crowdsourced` STTR

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Term representation:

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- System: for `xdx`: NS14 $>$ NS50 (very slight)

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- Collected 13,533 PDT responses from 499 participants;
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- Established feature weights and benchmark rankings;
  - Features and weights are reliable;
- Developed explainable semantic textual similarity system based on dependencies and tf-idf;
- Uncovered some exploitable patterns for predicting features and holistic quality;

Future work

With more data, I would:

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- Explore results for broader range of L1s;

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Future work

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- Explore results for broader range of L1s;
- Compare results across L2 English proficiency levels;
- Further map relationship between complexity and optimal settings;
- For a given PDT item, try clustering responses into multiple models;
  - Route NNS responses to most appropriate model;

Backup slides

(The following slides are all backup for Q&A.)

Research Questions (full)

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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?

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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?

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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)
The artist is drawing a pretty women. (Ch)
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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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  - I.e., *Acceptable* covered, *unacceptable* not covered;

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

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  - 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

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

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

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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*?
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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*;

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	.733	.601	.923	.808
Answerhood	.834	.721	.982	.936
Grammaticality	.861	.768	.960	.827
Interpretability	.818	.682	.919	.744
Verifiability	.845	.719	.968	.884
`Intransitive`	.863	.758	.978	.910
`Transitive`	.780	.653	.949	.853
`Ditransitive`	.812	.678	.924	.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

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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**

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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

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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**
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 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

Mean Average Precision

Average precision represents the area under the precision-recall curve. *Mean* average precision is an average over multiple average precisions (here it's from multiple PDT items or datasets).

This is a simplification, but for our purposes here, we can think of MAP as a measure of how well a ranking separates "yes" and "no" annotations.

Bad	Okay	Good
yes	**yes**	**yes**
no	**yes**	**yes**
no	no	**yes**
yes	**yes**	no
yes	no	no

	Bad	Okay	Good
AP $\rightarrow$	.51	.64	1.0

$$\text{MAP} = (0.51 + 0.64 + 1.00)/3 \approx 0.72$$

Predicting features: Answerhood MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.871	***.878***	.881	.869	.866	.868	**.874**	.881	.868
Tran	.816	.819	**.846**	.845	.838	.818	.823	***.851***	.845	.838
Ditr	.824	.826	***.841***	.837	.833	.821	.822	**.840**	.837	.833
Targ	.787	.788	**.810**	.817	.799	.787	.789	***.811***	.817	.798
Untg	.885	.890	***.900***	.892	.894	.883	.886	**.899**	.892	.895
Prim	.837	.840	***.854***	.854	.845	.837	.840	***.854***	.854	.846
Mix	.835	.838	***.857***	.854	.848	.833	.835	**.856**	.854	.847
Total	.836	.839	***.855***	.854	.847	.835	.838	**.855**	.854	.846

Predicting features: ANSWERHOOD MAP

	Crowd NS model = 14					Crowd NS model = 50				
	`ldh`	`xdh`	`xdx`	WAR	SBERT	`ldh`	`xdh`	`xdx`	WAR	SBERT
`Intr`	.868	.871	***.878***	.881	.869	.866	.868	**.874**	.881	.868
`Tran`	.816	.819	**.846**	.845	.838	.818	.823	***.851***	.845	.838
`Ditr`	.824	.826	***.841***	.837	.833	.821	.822	**.840**	.837	.833
`Targ`	.787	.788	**.810**	.817	.799	.787	.789	***.811***	.817	.798
`Untg`	.885	.890	***.900***	.892	.894	.883	.886	**.899**	.892	.895
`Prim`	.837	.840	***.854***	.854	.845	.837	.840	***.854***	.854	.846
`Mix`	.835	.838	***.857***	.854	.848	.833	.835	**.856**	.854	.847
Total	.836	.839	***.855***	.854	.847	.835	.838	**.855**	.854	.846

- `xdx` > `xdh` > `ldh`;

Predicting features: ANSWERHOOD MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.871	***.878***	.881	.869	.866	.868	**.874**	.881	.868
Tran	.816	.819	**.846**	.845	.838	.818	.823	***.851***	.845	.838
Ditr	.824	.826	***.841***	.837	.833	.821	.822	**.840**	.837	.833
Targ	.787	.788	**.810**	.817	.799	.787	.789	***.811***	.817	.798
Untg	.885	.890	***.900***	.892	.894	.883	.886	**.899**	.892	.895
Prim	.837	.840	***.854***	.854	.845	.837	.840	***.854***	.854	.846
Mix	.835	.838	***.857***	.854	.848	.833	.835	**.856**	.854	.847
Total	.836	.839	***.855***	.854	.847	.835	.838	**.855**	.854	.846

- xdx > xdh > ldh;
- Model size makes little difference;

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

Predicting features: ANSWERHOOD MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.871	***.882***	.881	.868	.869	.873	**.878**	.881	.870
Tran	.824	.826	***.852***	.845	.840	.817	.818	**.847**	.845	.840
Ditr	.820	.822	***.846***	.837	.832	.820	.822	**.845**	.837	.835
Targ	.786	.787	***.815***	.817	.798	.785	.787	**.813**	.817	.802
Untg	.889	.892	***.904***	.892	.896	.885	.889	**.900**	.892	.894
Total	.837	.840	***.860***	.854	.847	.835	.838	**.857**	.854	.848

Predicting features: Answerhood MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.871	***.882***	.881	.868	.869	.873	**.878**	.881	.870
Tran	.824	.826	***.852***	.845	.840	.817	.818	**.847**	.845	.840
Ditr	.820	.822	***.846***	.837	.832	.820	.822	**.845**	.837	.835
Targ	.786	.787	***.815***	.817	.798	.785	.787	**.813**	.817	.802
Untg	.889	.892	***.904***	.892	.896	.885	.889	**.900**	.892	.894
Total	.837	.840	***.860***	.854	.847	.835	.838	**.857**	.854	.848

- xdx > xdh > ldh;

Predicting features: Answerhood MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.871	***.882***	.881	.868	.869	.873	**.878**	.881	.870
Tran	.824	.826	***.852***	.845	.840	.817	.818	**.847**	.845	.840
Ditr	.820	.822	***.846***	.837	.832	.820	.822	**.845**	.837	.835
Targ	.786	.787	***.815***	.817	.798	.785	.787	**.813**	.817	.802
Untg	.889	.892	***.904***	.892	.896	.885	.889	**.900**	.892	.894
Total	.837	.840	***.860***	.854	.847	.835	.838	**.857**	.854	.848

- xdx > xdh > ldh;
- familiar > crowdsourced;

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

Predicting features: Grammaticality MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.870	***.872***	.887	.866	.863	.864	**.866**	.887	.864
Tran	.753	.756	**.757**	.781	.757	.758	.760	***.761***	.781	.757
Ditr	.682	.685	***.700***	.695	.694	.679	.685	**.697**	.695	.693
Targ	.777	.778	***.784***	.800	.782	.776	.776	**.783**	.800	.781
Untg	.758	.763	***.769***	.776	.762	.757	.762	**.766**	.776	.761
Prim	.769	.773	***.776***	.788	.770	.768	.770	**.774**	.788	.770
Mix	.766	.768	***.776***	.788	.774	.765	.768	**.775**	.788	.772
Total	.768	.770	***.776***	.788	.772	.767	.769	**.775**	.788	.771

Predicting features: GRAMMATICALITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	`ldh`	`xdh`	`xdx`	WAR	SBERT	`ldh`	`xdh`	`xdx`	WAR	SBERT
`Intr`	.868	.870	***.872***	.887	.866	.863	.864	**.866**	.887	.864
`Tran`	.753	.756	**.757**	.781	.757	.758	.760	***.761***	.781	.757
`Ditr`	.682	.685	***.700***	.695	.694	.679	.685	**.697**	.695	.693
`Targ`	.777	.778	***.784***	.800	.782	.776	.776	**.783**	.800	.781
`Untg`	.758	.763	***.769***	.776	.762	.757	.762	**.766**	.776	.761
`Prim`	.769	.773	***.776***	.788	.770	.768	.770	**.774**	.788	.770
`Mix`	.766	.768	***.776***	.788	.774	.765	.768	**.775**	.788	.772
Total	.768	.770	***.776***	.788	.772	.767	.769	**.775**	.788	.771

In *most* cases:

Predicting features: GRAMMATICALITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.868	.870	***.872***	.887	.866	.863	.864	**.866**	.887	.864
Tran	.753	.756	**.757**	.781	.757	.758	.760	***.761***	.781	.757
Ditr	.682	.685	***.700***	.695	.694	.679	.685	**.697**	.695	.693
Targ	.777	.778	***.784***	.800	.782	.776	.776	**.783**	.800	.781
Untg	.758	.763	***.769***	.776	.762	.757	.762	**.766**	.776	.761
Prim	.769	.773	***.776***	.788	.770	.768	.770	**.774**	.788	.770
Mix	.766	.768	***.776***	.788	.774	.765	.768	**.775**	.788	.772
Total	.768	.770	***.776***	.788	.772	.767	.769	**.775**	.788	.771

In *most* cases:

- xdx > xdh > ldh;

Predicting features: GRAMMATICALITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	`ldh`	`xdh`	`xdx`	WAR	SBERT	`ldh`	`xdh`	`xdx`	WAR	SBERT
`Intr`	.868	.870	***.872***	.887	.866	.863	.864	**.866**	.887	.864
`Tran`	.753	.756	**.757**	.781	.757	.758	.760	***.761***	.781	.757
`Ditr`	.682	.685	***.700***	.695	.694	.679	.685	**.697**	.695	.693
`Targ`	.777	.778	***.784***	.800	.782	.776	.776	**.783**	.800	.781
`Untg`	.758	.763	***.769***	.776	.762	.757	.762	**.766**	.776	.761
`Prim`	.769	.773	***.776***	.788	.770	.768	.770	**.774**	.788	.770
`Mix`	.766	.768	***.776***	.788	.774	.765	.768	**.775**	.788	.772
Total	.768	.770	***.776***	.788	.772	.767	.769	**.775**	.788	.771

In *most* cases:

- `xdx` > `xdh` > `ldh`;

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

Predicting features: GRAMMATICALITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.863	.864	**.873**	.887	.863	.868	.869	***.874***	.887	.869
Tran	.760	.759	***.762***	.781	.760	.752	.754	**.757**	.781	.758
Ditr	.678	.685	**.698**	.695	.698	.678	.680	***.699***	.695	.696
Targ	.776	.776	***.787***	.800	.783	.776	.777	**.786**	.800	.786
Untg	.757	.762	***.768***	.776	.764	.756	.759	**.767**	.776	.763
Total	.767	.769	***.778***	.788	.773	.766	.768	**.776**	.788	.774

Predicting features: Grammaticality MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.863	.864	***.873***	.887	.863	.868	.869	***.874***	.887	.869
Tran	.760	.759	***.762***	.781	.760	.752	.754	**.757**	.781	.758
Ditr	.678	.685	**.698**	.695	.698	.678	.680	***.699***	.695	.696
Targ	.776	.776	***.787***	.800	.783	.776	.777	**.786**	.800	.786
Untg	.757	.762	***.768***	.776	.764	.756	.759	**.767**	.776	.763
Total	.767	.769	***.778***	.788	.773	.766	.768	**.776**	.788	.774

In *most* cases:

Predicting features: GRAMMATICALITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.863	.864	**.873**	.887	.863	.868	.869	***.874***	.887	.869
Tran	.760	.759	***.762***	.781	.760	.752	.754	**.757**	.781	.758
Ditr	.678	.685	**.698**	.695	.698	.678	.680	***.699***	.695	.696
Targ	.776	.776	***.787***	.800	.783	.776	.777	**.786**	.800	.786
Untg	.757	.762	***.768***	.776	.764	.756	.759	**.767**	.776	.763
Total	.767	.769	***.778***	.788	.773	.766	.768	**.776**	.788	.774

In *most* cases:

- xdx > xdh > ldh;

Predicting features: GRAMMATICALITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	`ldh`	`xdh`	`xdx`	WAR	SBERT	`ldh`	`xdh`	`xdx`	WAR	SBERT
`Intr`	.863	.864	**.873**	.887	.863	.868	.869	***.874***	.887	.869
`Tran`	.760	.759	***.762***	.781	.760	.752	.754	**.757**	.781	.758
`Ditr`	.678	.685	**.698**	.695	.698	.678	.680	***.699***	.695	.696
`Targ`	.776	.776	***.787***	.800	.783	.776	.777	**.786**	.800	.786
`Untg`	.757	.762	***.768***	.776	.764	.756	.759	**.767**	.776	.763
Total	.767	.769	***.778***	.788	.773	.766	.768	**.776**	.788	.774

In *most* cases:

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

Predicting features: GRAMMATICALITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.863	.864	**.873**	.887	.863	.868	.869	***.874***	.887	.869
Tran	.760	.759	***.762***	.781	.760	.752	.754	**.757**	.781	.758
Ditr	.678	.685	**.698**	.695	.698	.678	.680	***.699***	.695	.696
Targ	.776	.776	***.787***	.800	.783	.776	.777	**.786**	.800	.786
Untg	.757	.762	***.768***	.776	.764	.756	.759	**.767**	.776	.763
Total	.767	.769	***.778***	.788	.773	.766	.768	**.776**	.788	.774

In *most* cases:

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

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

Predicting features: INTERPRETABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.932	.931	***.933***	.930	.922	.928	.927	**.933**	.930	.923
Tran	***.823***	.821	.811	.803	.806	**.821**	.816	.812	.803	.804
Ditr	.789	.784	***.794***	.721	.777	.786	.782	**.792**	.721	.772
Targ	.835	.832	***.836***	.804	.828	.833	.829	**.834**	.804	.826
Untg	***.862***	.858	.856	.833	.842	**.857**	.855	**.857**	.833	.840
Prim	***.847***	.845	.846	.818	.837	.845	.842	**.846**	.818	.833
Mix	***.849***	.846	.846	.818	.833	.844	.841	**.845**	.818	.833
Total	***.848***	.845	.846	.818	.835	**.845**	.842	**.845**	.818	.833

Predicting features: INTERPRETABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.932	.931	***.933***	.930	.922	.928	.927	**.933**	.930	.923
Tran	***.823***	.821	.811	.803	.806	**.821**	.816	.812	.803	.804
Ditr	.789	.784	***.794***	.721	.777	.786	.782	**.792**	.721	.772
Targ	.835	.832	***.836***	.804	.828	.833	.829	**.834**	.804	.826
Untg	***.862***	.858	.856	.833	.842	**.857**	.855	**.857**	.833	.840
Prim	***.847***	.845	.846	.818	.837	.845	.842	**.846**	.818	.833
Mix	***.849***	.846	.846	.818	.833	.844	.841	**.845**	.818	.833
Total	***.848***	.845	.846	.818	.835	**.845**	.842	**.845**	.818	.833

- 14NS crowdsourced > 50NS crowdsourced;

Predicting features: INTERPRETABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.932	.931	***.933***	.930	.922	.928	.927	**.933**	.930	.923
Tran	***.823***	.821	.811	.803	.806	**.821**	.816	.812	.803	.804
Ditr	.789	.784	***.794***	.721	.777	.786	.782	**.792**	.721	.772
Targ	.835	.832	***.836***	.804	.828	.833	.829	**.834**	.804	.826
Untg	***.862***	.858	.856	.833	.842	**.857**	.855	**.857**	.833	.840
Prim	***.847***	.845	.846	.818	.837	.845	.842	**.846**	.818	.833
Mix	***.849***	.846	.846	.818	.833	.844	.841	**.845**	.818	.833
Total	***.848***	.845	.846	.818	.835	**.845**	.842	**.845**	.818	.833

- 14NS crowdsourced > 50NS crowdsourced;
- intransitives & ditransitives work best with xdx;

Predicting features: INTERPRETABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.932	.931	***.933***	.930	.922	.928	.927	**.933**	.930	.923
Tran	***.823***	.821	.811	.803	.806	**.821**	.816	.812	.803	.804
Ditr	.789	.784	***.794***	.721	.777	.786	.782	**.792**	.721	.772
Targ	.835	.832	***.836***	.804	.828	.833	.829	**.834**	.804	.826
Untg	***.862***	.858	.856	.833	.842	**.857**	.855	**.857**	.833	.840
Prim	***.847***	.845	.846	.818	.837	.845	.842	**.846**	.818	.833
Mix	***.849***	.846	.846	.818	.833	.844	.841	**.845**	.818	.833
Total	***.848***	.845	.846	.818	.835	**.845**	.842	**.845**	.818	.833

- 14NS crowdsourced > 50NS crowdsourced;
- intransitives & ditransitives work best with xdx;
- transitives work best with ldh;

Predicting features: INTERPRETABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.932	.931	***.933***	.930	.922	.928	.927	**.933**	.930	.923
Tran	***.823***	.821	.811	.803	.806	**.821**	.816	.812	.803	.804
Ditr	.789	.784	***.794***	.721	.777	.786	.782	**.792**	.721	.772
Targ	.835	.832	***.836***	.804	.828	.833	.829	**.834**	.804	.826
Untg	***.862***	.858	.856	.833	.842	**.857**	.855	**.857**	.833	.840
Prim	***.847***	.845	.846	.818	.837	.845	.842	**.846**	.818	.833
Mix	***.849***	.846	.846	.818	.833	.844	.841	**.845**	.818	.833
Total	***.848***	.845	.846	.818	.835	**.845**	.842	**.845**	.818	.833

- 14NS crowdsourced > 50NS crowdsourced;
- intransitives & ditransitives work best with xdx;
- transitives work best with ldh;
  - Why? Transitive responses are relatively homogenous; Annotators relatively strict;

Predicting features: Interpretability MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.930	.930	***.934***	.930	.923	**.933**	.931	.932	.930	.922
Tran	**.822**	.819	.811	.803	.805	***.826***	.824	.811	.803	.805
Ditr	.787	.786	***.796***	.721	.782	.788	.783	**.795**	.721	.772
Targ	.835	.833	***.836***	.804	.830	**.835**	.832	**.835**	.804	.825
Untg	**.858**	.857	**.858**	.833	.843	***.863***	.859	.857	.833	.841
Total	**.847**	.845	**.847**	.818	.837	***.849***	.846	.846	.818	.833

Predicting features: Interpretability MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.930	.930	***.934***	.930	.923	**.933**	.931	.932	.930	.922
Tran	**.822**	.819	.811	.803	.805	***.826***	.824	.811	.803	.805
Ditr	.787	.786	***.796***	.721	.782	.788	.783	**.795**	.721	.772
Targ	.835	.833	***.836***	.804	.830	**.835**	.832	**.835**	.804	.825
Untg	**.858**	.857	**.858**	.833	.843	***.863***	.859	.857	.833	.841
Total	**.847**	.845	**.847**	.818	.837	***.849***	.846	.846	.818	.833

- 14NS crowdsourced > 14NS familiar;

Predicting features: INTERPRETABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.930	.930	***.934***	.930	.923	**.933**	.931	.932	.930	.922
Tran	**.822**	.819	.811	.803	.805	***.826***	.824	.811	.803	.805
Ditr	.787	.786	***.796***	.721	.782	.788	.783	**.795**	.721	.772
Targ	.835	.833	***.836***	.804	.830	**.835**	.832	**.835**	.804	.825
Untg	**.858**	.857	**.858**	.833	.843	***.863***	.859	.857	.833	.841
Total	**.847**	.845	**.847**	.818	.837	***.849***	.846	.846	.818	.833

- 14NS crowdsourced > 14NS familiar;
- intransitives & ditransitives work best with xdx;

Predicting features: INTERPRETABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.930	.930	***.934***	.930	.923	**.933**	.931	.932	.930	.922
Tran	**.822**	.819	.811	.803	.805	***.826***	.824	.811	.803	.805
Ditr	.787	.786	***.796***	.721	.782	.788	.783	**.795**	.721	.772
Targ	.835	.833	***.836***	.804	.830	**.835**	.832	**.835**	.804	.825
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Total	**.847**	.845	**.847**	.818	.837	***.849***	.846	.846	.818	.833

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Predicting features: INTERPRETABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.930	.930	***.934***	.930	.923	**.933**	.931	.932	.930	.922
Tran	**.822**	.819	.811	.803	.805	***.826***	.824	.811	.803	.805
Ditr	.787	.786	***.796***	.721	.782	.788	.783	**.795**	.721	.772
Targ	.835	.833	***.836***	.804	.830	**.835**	.832	**.835**	.804	.825
Untg	**.858**	.857	**.858**	.833	.843	***.863***	.859	.857	.833	.841
Total	**.847**	.845	**.847**	.818	.837	***.849***	.846	.846	.818	.833

- 14NS crowdsourced > 14NS familiar;
- intransitives & ditransitives work best with xdx;
- transitives work best with ldh;
  - Why? Transitive responses are relatively homogenous; Annotators relatively strict;

Predicting features: VERIFIABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.852	.852	***.853***	.866	.840	.849	.849	**.851**	.866	.836
Tran	***.809***	.808	.803	.798	.787	**.807**	.806	.803	.798	.785
Ditr	.814	.812	***.815***	.780	.798	.811	.809	**.812**	.780	.796
Targ	***.825***	.824	.825	.815	.812	**.825**	.824	.823	.815	.810
Untg	***.825***	.824	.822	.815	.805	**.820**	.819	.820	.815	.802
Prim	***.826***	.824	.823	.815	.808	**.824**	.823	.822	.815	.806
Mix	***.825***	.824	.824	.815	.808	**.821**	.821	.821	.815	.805
Total	***.825***	.824	.824	.815	.808	**.823**	.822	.822	.815	.806

Predicting features: VERIFIABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.852	.852	***.853***	.866	.840	.849	.849	**.851**	.866	.836
Tran	***.809***	.808	.803	.798	.787	**.807**	.806	.803	.798	.785
Ditr	.814	.812	***.815***	.780	.798	.811	.809	**.812**	.780	.796
Targ	***.825***	.824	.825	.815	.812	**.825**	.824	.823	.815	.810
Untg	***.825***	.824	.822	.815	.805	**.820**	.819	.820	.815	.802
Prim	***.826***	.824	.823	.815	.808	**.824**	.823	.822	.815	.806
Mix	***.825***	.824	.824	.815	.808	**.821**	.821	.821	.815	.805
Total	***.825***	.824	.824	.815	.808	**.823**	.822	.822	.815	.806

- 14NS crowd > 50NS crowd;

Predicting features: Verifiability MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.852	.852	***.853***	.866	.840	.849	.849	**.851**	.866	.836
Tran	***.809***	.808	.803	.798	.787	**.807**	.806	.803	.798	.785
Ditr	.814	.812	***.815***	.780	.798	.811	.809	**.812**	.780	.796
Targ	***.825***	.824	.825	.815	.812	**.825**	.824	.823	.815	.810
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Mix	***.825***	.824	.824	.815	.808	**.821**	.821	.821	.815	.805
Total	***.825***	.824	.824	.815	.808	**.823**	.822	.822	.815	.806

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

Predicting features: Verifiability MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.852	.852	***.853***	.866	.840	.849	.849	**.851**	.866	.836
Tran	***.809***	.808	.803	.798	.787	**.807**	.806	.803	.798	.785
Ditr	.814	.812	***.815***	.780	.798	.811	.809	**.812**	.780	.796
Targ	***.825***	.824	.825	.815	.812	**.825**	.824	.823	.815	.810
Untg	***.825***	.824	.822	.815	.805	**.820**	.819	.820	.815	.802
Prim	***.826***	.824	.823	.815	.808	**.824**	.823	.822	.815	.806
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Total	***.825***	.824	.824	.815	.808	**.823**	.822	.822	.815	.806

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Predicting features: VERIFIABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.852	.852	***.853***	.866	.840	.849	.849	**.851**	.866	.836
Tran	***.809***	.808	.803	.798	.787	**.807**	.806	.803	.798	.785
Ditr	.814	.812	***.815***	.780	.798	.811	.809	**.812**	.780	.796
Targ	***.825***	.824	.825	.815	.812	**.825**	.824	.823	.815	.810
Untg	***.825***	.824	.822	.815	.805	**.820**	.819	.820	.815	.802
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Mix	***.825***	.824	.824	.815	.808	**.821**	.821	.821	.815	.805
Total	***.825***	.824	.824	.815	.808	**.823**	.822	.822	.815	.806

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  - Why? Transitive responses are relatively homogenous; Annotators relatively strict;

Predicting features: Verifiability MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.847	.847	**.852**	.866	.836	.852	.852	***.854***	.866	.843
Tran	***.808***	.807	.803	.798	.787	**.807**	.807	.802	.798	.786
Ditr	.811	.811	**.812**	.780	.802	.815	.812	***.817***	.780	.796
Targ	.821	.821	**.822**	.815	.814	.824	.824	***.826***	.815	.811
Untg	**.824**	.822	.823	.815	.803	***.825***	.824	.823	.815	.806
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Predicting features: VERIFIABILITY MAP

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	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
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Tran	***.808***	.807	.803	.798	.787	**.807**	.807	.802	.798	.786
Ditr	.811	.811	**.812**	.780	.802	.815	.812	***.817***	.780	.796
Targ	.821	.821	**.822**	.815	.814	.824	.824	***.826***	.815	.811
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Total	.822	.822	**.823**	.815	.808	***.825***	.824	.824	.815	.808

- 14NS crowd > 14NS familiar;

Predicting features: VERIFIABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
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- 14NS crowd > 14NS familiar;
- intransitives & ditransitives work best with xdx;

Predicting features: VERIFIABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
Intr	.847	.847	**.852**	.866	.836	.852	.852	***.854***	.866	.843
Tran	***.808***	.807	.803	.798	.787	**.807**	.807	.802	.798	.786
Ditr	.811	.811	**.812**	.780	.802	.815	.812	***.817***	.780	.796
Targ	.821	.821	**.822**	.815	.814	.824	.824	***.826***	.815	.811
Untg	**.824**	.822	.823	.815	.803	***.825***	.824	.823	.815	.806
Total	.822	.822	**.823**	.815	.808	***.825***	.824	.824	.815	.808

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	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
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Tran	***.808***	.807	.803	.798	.787	**.807**	.807	.802	.798	.786
Ditr	.811	.811	**.812**	.780	.802	.815	.812	***.817***	.780	.796
Targ	.821	.821	**.822**	.815	.814	.824	.824	***.826***	.815	.811
Untg	**.824**	.822	.823	.815	.803	***.825***	.824	.823	.815	.806
Total	.822	.822	**.823**	.815	.808	***.825***	.824	.824	.815	.808

- 14NS crowd > 14NS familiar;
- intransitives & ditransitives work best with xdx;
- transitives work best with ldh;
  - Why? Transitive responses are relatively homogenous; Annotators relatively strict;

Predicting quality: `Targeting`

Spearman rank correlations: System vs. WAR (benchmark)

		`targeted`		`untargeted`	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	**.380**	.530	.300	.444
	median	**.369**	.545	.314	.472
50NS	mean	***.393***	.550	*.305*	.469
	median	***.389***	.564	*.323*	.496

Predicting quality: `Targeting`

Spearman rank correlations: System vs. WAR (benchmark)

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		System	SBERT	System	SBERT
	count	180	60	180	60
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	median	***.389***	.564	*.323*	.496

- `targeted` $>$ `untargeted`

Predicting quality: `Targeting`

Spearman rank correlations: System vs. WAR (benchmark)

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50NS	mean	***.393***	.550	*.305*	.469
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- `targeted` > `untargeted`
- 50NS models > 14NS models

Predicting quality: `Targeting`

Spearman rank correlations: System vs. WAR (benchmark)

		`targeted`		`untargeted`	
		System	SBERT	System	SBERT
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	median	**.369**	.545	.314	.472
50NS	mean	***.393***	.550	*.305*	.469
	median	***.389***	.564	*.323*	.496

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

Predicting quality: `Familiarity`

Spearman rank correlations: System vs. WAR (benchmark)

		familiar		crowdsourced	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.338	.499	**.339**	.481
	median	**.329**	.513	.326	.500

Predicting quality: `Familiarity`

Spearman rank correlations: System vs. WAR (benchmark)

		`familiar`		`crowdsourced`	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.338	.499	**.339**	.481
	median	**.329**	.513	.326	.500

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

Predicting quality: `Familiarity`

Spearman rank correlations: System vs. WAR (benchmark)

		`familiar`		`crowdsourced`	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.338	.499	**.339**	.481
	median	**.329**	.513	.326	.500

- System: No discernible difference for `familiar` vs `crowdsourced`
- SBERT: `familiar` $>$ `crowdsourced`

Predicting quality: `Familiarity`

Spearman rank correlations: System vs. WAR (benchmark)

		familiar		crowdsourced	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.338	.499	**.339**	.481
	median	**.329**	.513	.326	.500

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

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		primary		mixed	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.339	.493	**.340**	.481
14NS	median	.326	.517	**.334**	.500
50NS	mean	***.354***	.514	.344	.505
50NS	median	.345	.532	***.350***	.518

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		`primary`		`mixed`	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.339	.493	**.340**	.481
14NS	median	.326	.517	**.334**	.500
50NS	mean	***.354***	.514	.344	.505
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Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

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		System	SBERT	System	SBERT
	count	180	60	180	60
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14NS	median	.326	.517	**.334**	.500
50NS	mean	***.354***	.514	.344	.505
50NS	median	.345	.532	***.350***	.518

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

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		primary		mixed	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.339	.493	**.340**	.481
	median	.326	.517	**.334**	.500
50NS	mean	***.354***	.514	.344	.505
	median	.345	.532	***.350***	.518

- System: 14NS: `primary` < `mixed` (slight difference)
- System: 50NS: `primary` ≈ `mixed`

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		primary		mixed	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.339	.493	**.340**	.481
	median	.326	.517	**.334**	.500
50NS	mean	***.354***	.514	.344	.505
	median	.345	.532	***.350***	.518

- System: 14NS: `primary` $<$ `mixed` (slight difference)
- System: 50NS: `primary` $\approx$ `mixed`
- SBERT: `primary` $>$ `mixed`

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		primary		mixed	
		System	SBERT	System	SBERT
	count	180	60	180	60
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- System: 14NS: `primary` < `mixed` (slight difference)
- System: 50NS: `primary` ≈ `mixed`
- SBERT: `primary` > `mixed`
- System & SBERT: 50NS > 14NS

Predicting quality: `Primacy`

Spearman rank correlations: System vs. WAR (benchmark)

		primary		mixed	
		System	SBERT	System	SBERT
	count	180	60	180	60
14NS	mean	.339	.493	**.340**	.481
14NS	median	.326	.517	**.334**	.500
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- System: 14NS: `primary` < `mixed` (slight difference)
- System: 50NS: `primary` ≈ `mixed`
- SBERT: `primary` > `mixed`
- System & SBERT: 50NS > 14NS
  - System: model size effect is greatest for `primary`

Predicting quality: `Term Representation`

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		`ldh`	`xdh`	`xdx`	(text)
	count	120	120	120	40
14NS	mean	.333	.336	***.351***	.487
	median	.318	**.344**	.330	.507
50NS	mean	***.350***	*.349*	.348	.509
	median	*.364*	***.374***	*.331*	.523

Predicting quality: `Term Representation`

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		`ldh`	`xdh`	`xdx`	(text)
	count	120	120	120	40
14NS	mean	.333	.336	***.351***	.487
	median	.318	**.344**	.330	.507
50NS	mean	***.350***	*.349*	.348	.509
	median	*.364*	***.374***	*.331*	.523

- SBERT: 50NS > 14NS

Predicting quality: `Term Representation`

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		`ldh`	`xdh`	`xdx`	(text)
	count	120	120	120	40
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	median	.318	**.344**	.330	.507
50NS	mean	***.350***	*.349*	.348	.509
	median	*.364*	***.374***	*.331*	.523

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

Predicting quality: `Term Representation`

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		`ldh`	`xdh`	`xdx`	(text)
	count	120	120	120	40
14NS	mean	.333	.336	***.351***	.487
	median	.318	**.344**	.330	.507
50NS	mean	***.350***	*.349*	.348	.509
	median	*.364*	***.374***	*.331*	.523

- SBERT: 50NS $>$ 14NS
- System: for `ldh` & `xdh`: 50NS $>$ 14NS;
  - Model size effect is greater for `ldh`

Predicting quality: `Term Representation`

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		`ldh`	`xdh`	`xdx`	(text)
	count	120	120	120	40
14NS	mean	.333	.336	***.351***	.487
14NS	median	.318	**.344**	.330	.507
50NS	mean	***.350***	*.349*	.348	.509
50NS	median	*.364*	***.374***	*.331*	.523

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

Predicting quality: Term Normalization

Response A	Response B	Non-norm -alized weight	Normal -ized weight
The girl is singing	The girl in the cute purple dress is singing a song		
det(the, girl)	det(the, girl)	.143 (2/14)	.175
nsubj(girl, sing)	nsubj(girl, sing)	.143	.175
	det(the, dress)	.071	.050
	amod(cute, dress)	**.071** (1/14)	**.050**
	amod(purple, dress)	**.071**	**.050**
	prep_in(dress, girl)	.071	.050
aux(be, sing)	aux(be, sing)	.143	.175
root(sing, ROOT)	root(sing, ROOT)	.143	.175
	det(a, song)	.071	.050
	dobj(song, sing)	.071	.050
4	10	1.0 (14/14)	1.0

A 2-response toy NS model. Normalizing for response length so each *response* (not *dependency*) in model carries equal weight reduces weight of some extraneous dependencies, but performance suffers overall.