

Semantic Analysis of Image-Based Learner Sentences

Levi King
Indiana University

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

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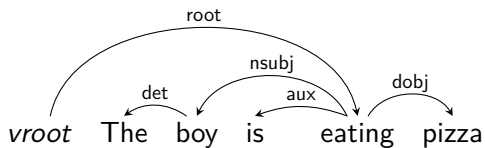
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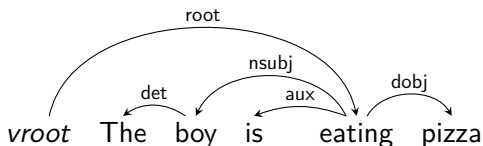
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- RQ6. What is the annotation scheme for this task and can the system perform within the range of human performance?

System

Step 1: Dependency parse:



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Get dependencies:

root(eating, *vroot*)

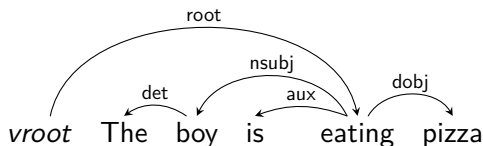
det(the, boy)

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Step 2: Lemmatize:

→ root(**eat**, *vroot*)

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	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

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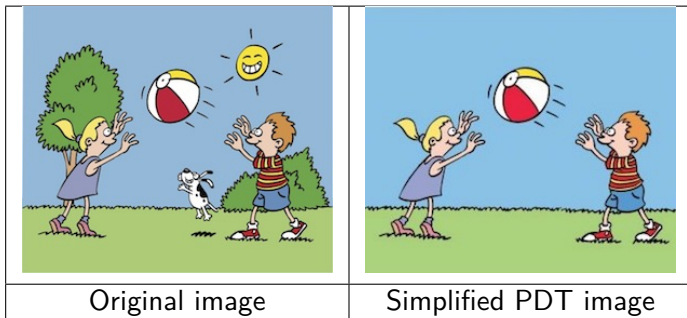
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NNS 1: 0.139; NNS 2: 0.886 \rightarrow *NNS 2 is closest to the model.*

Data collection



PDT with very simple images only:



Intended to focus participants' attention on the main action

Data collection




Two PDT prompt versions:

Targeted	Untargeted
	
<i>What is the baby doing?</i>	<i>What is happening?</i>

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 <i>cleaning</i> the street.
	a man <i>removing</i> the tree leafs.
	The man is <i>sweeping</i> the floor.
	A man is <i>gathering</i> 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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Annotation features

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

					
<i>What is the boy doing?</i>	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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- ▶ Determine feature weights and apply to annotations to obtain benchmark holistic scores and then rankings.
- ▶ 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)

<i>What is happening?</i>	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
x dh	.658	.661	.660	.572
l dh	.665	.664	.671	.578
Total	.576	.583	.584	.505

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xdx	.364	.424	.421	.364
x dh	.658	.661	.660	.572
l dh	.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.:

$\text{Intrans} < \text{Trans} < \text{Ditrans}$

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
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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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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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Untg	.768	.763	.765	.777	.740	.762	.759	.763	.777	.736
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 - ▶ ditrans, untarg: *most complex*—i.e., highest STTRs;
 - ▶ In general: ldh STTR > x dh STTR > x dx STTR

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	ldh	xdh	xdx	WAR	SBERT	ldh	xdh	xdx	WAR	SBERT
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
Targ	.733	.732	.732	.735	.707	.739	.736	.733	.735	.709
Untg	.767	.764	.769	.777	.737	.767	.761	.767	.777	.742
Total	.750	.748	.751	.756	.722	.753	.749	.750	.756	.725

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- *mixed only (due to sparse familiar data);

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For all 5 features, my system outperforms SBERT.

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

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INTERPRETABILITY:

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Predicting features: MAP Results

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Predicting features: MAP Results

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- ▶ intransitives & ditransitives work best with xdx;

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For both INTERPRETABILITY & VERIFIABILITY:

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

Predicting quality

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Holistic quality 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:

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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
50NS	mean	.423	.516	.345	.566	.278	.446
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- ▶ System, regardless of model size: intrans > trans > ditrans;
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 - ▶ trans & ditrans: 50NS model is best;
 - ▶ intrans: 14NS gives best mean, 50NS gives best median;

Predicting quality: Results

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Targeting:

Predicting quality: Results

Targeting:

- ▶ `targeted > untargeted`

Predicting quality: Results

Targeting:

- ▶ targeted > untargeted
- ▶ 50NS models > 14NS models

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Familiarity (14NS models only):

Predicting quality: Results

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Familiarity (14NS models only):

- ▶ System: No discernible difference for familiar vs crowdsourced

Predicting quality: Results

Targeting:

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- ▶ 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

Predicting quality: 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

Predicting quality: Results

Predicting quality: Results

Primacy:

Predicting quality: Results

Primacy:

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

Predicting quality: Results

Primacy:

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

Predicting quality: Results

Primacy:

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

Predicting quality: Results

Primacy:

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

Predicting quality: 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

Predicting quality: Results

Primacy:

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Term representation:

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- ▶ System: for 1dh & xdh: 50NS > 14NS;
 - ▶ Model size effect is greater for 1dh
- ▶ System: for xdx: NS14 > NS50 (very slight)

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- ▶ Developed explainable semantic textual similarity system based on dependencies and tf-idf;
- ▶ Uncovered some exploitable patterns for predicting features and holistic quality;

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With more data, I would:

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 - ▶ 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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- 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)
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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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- ▶ Rank by scores & calculate Mean Average Precision (MAP);
 - ▶ MAP *acceptable* responses: $\approx 51\%$
- ▶ 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	familiar	primary	ldh
transitive	untargeted	crowdsourced	mixed	x dh
ditransitive				x dx

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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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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<i>What is the boy doing?</i>	Pref?	Core	Ansr	Gram	Intrp	Verif
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He may get fat eating.	no	0	0	1	1	0

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He is hungry.	no	0	0	1	0	1
the boy is eating pizza	yes	1	1	1	1	1

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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

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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

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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

AP →	.51	.64	1.0
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$$\text{MAP} = (0.51 + 0.64 + 1.00)/3 \approx 0.72$$

Predicting features: ANSWERHOOD MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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

► $x dx > x dh > ldh$;

Predicting features: ANSWERHOOD MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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

- ▶ $x dx > x dh > ldh$;
- ▶ 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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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

- ▶ $x dx > x dh > ldh$;
- ▶ 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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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:

- $x dx > x dh > ldh$;

Predicting features: GRAMMATICALITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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:

- $x dx > x dh > ldh$;

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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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:

- ▶ $x dx > x dh > ldh$;
- ▶ familiar 14NS > crowd 14NS > crowd 50NS;

Predicting features: GRAMMATICALITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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:

- ▶ $x dx > x dh > ldh$;
- ▶ 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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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
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;

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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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
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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;
- ▶ intransitives & ditransitives work best with xdx;

Predicting features: VERIFIABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	WAR	SBERT
Intr	.852	.852	.853	.866	.840	.849	.849	.851	.866	.836
Tran	.809	.808	.803	.798	.787	.807	.806	.803	.798	.785
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Total	.825	.824	.824	.815	.808	.823	.822	.822	.815	.806

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

Predicting features: VERIFIABILITY MAP

	Crowd NS model = 14					Crowd NS model = 50				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	WAR	SBERT
Intr	.852	.852	.853	.866	.840	.849	.849	.851	.866	.836
Tran	.809	.808	.803	.798	.787	.807	.806	.803	.798	.785
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Mix	.825	.824	.824	.815	.808	.821	.821	.821	.815	.805
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- ▶ 14NS crowd > 50NS crowd;
- ▶ intransitives & ditransitives work best with xdx;
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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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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

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
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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;

Predicting features: VERIFIABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	WAR	SBERT
Intr	.847	.847	.852	.866	.836	.852	.852	.854	.866	.843
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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	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	WAR	SBERT
Intr	.847	.847	.852	.866	.836	.852	.852	.854	.866	.843
Tran	.808	.807	.803	.798	.787	.807	.807	.802	.798	.786
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Total	.822	.822	.823	.815	.808	.825	.824	.824	.815	.808

- ▶ 14NS crowd > 14NS familiar;
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- ▶ transitives work best with ldh;

Predicting features: VERIFIABILITY MAP

	Familiar NS model = 14					Crowd NS model = 14				
	ldh	x dh	x dx	WAR	SBERT	ldh	x dh	x dx	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

- ▶ 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)

		targeted		untargeted	
		System	SBERT	System	SBERT
	count	180	60	180	60
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50NS	mean	.393	.550	.305	.469
	median	.389	.564	.323	.496

► targeted > untargeted

Predicting quality: Targeting

Spearman rank correlations: System vs. WAR (benchmark)

		targeted		untargeted	
		System	SBERT	System	SBERT
	count	180	60	180	60
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50NS	mean	.393	.550	.305	.469
	median	.389	.564	.323	.496

- ▶ targeted > untargeted
- ▶ 50NS models > 14NS models

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

- ▶ 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
	median	.326	.517	.334	.500
50NS	mean	.354	.514	.344	.505
	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
	median	.326	.517	.334	.500
50NS	mean	.354	.514	.344	.505
	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
	median	.326	.517	.334	.500
50NS	mean	.354	.514	.344	.505
	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 \approx 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
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
- ▶ 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
	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
- ▶ 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
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
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
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;

Predicting quality: Term Representation

Spearman rank correlations: System vs. WAR (benchmark)

		System			SBERT
		1dh	xdh	xdx	(text)
		count	120	120	120
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 1dh & xdh: 50NS > 14NS;
 - ▶ Model size effect is greater for 1dh

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
- ▶ 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
	doobj(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.