

Entailment above the word level in distributional semantics

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Summary

Entailment among composite phrases rather than nouns.
(Cheap training data!)

Entailment among logical words rather than content words.
(Part of Recognizing Textual Entailment?)

Different entailment relations at different semantic types.
(Prediction from formal semantics.)

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AN	⊨	N	→	N	⊨	N
big cat		cat		dog		animal

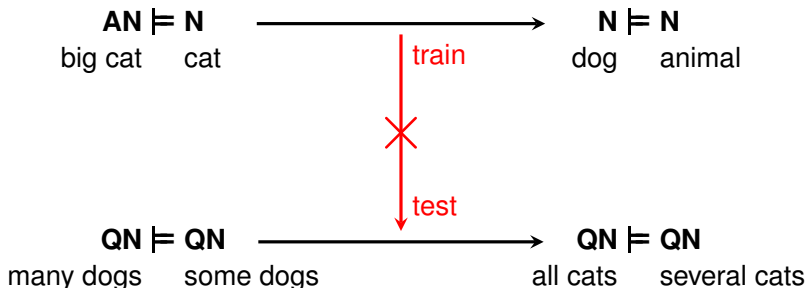
QN	⊨	QN	train	test	QN	⊨	QN
many dogs		some dogs			all cats		several cats

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Approaches to semantics

“In order to say what a meaning *is*,
we may first ask what a meaning *does*,
and then find something that does that.” —David Lewis

Approaches to semantics

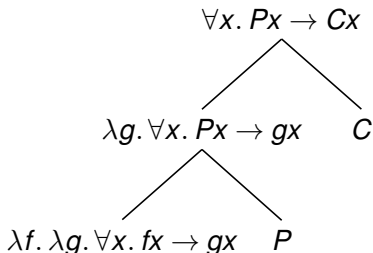
“In order to say what a meaning *is*,
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Truth, entailment

Every person cried. \models Every professor cried.

A person cried. $\not\models$ A professor cried.

Formal semantics



Approaches to semantics

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Concepts, similarity

ambulance \sim battleship

ambulance \approx bookstore

Distributional semantics

	abandon	abdominal	ability	academic	accept	...
ambulance	27	10	50	17	130	...
battleship	35	0	32	1	25	...
bookstore	5	0	6	33	13	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮

衆賢
探象之圖



Distributional semantics for entailment among words

For each word w , rank contexts c by descending $\frac{\Pr(c | w)}{\Pr(c)} > 1$.

“pointwise mutual information”

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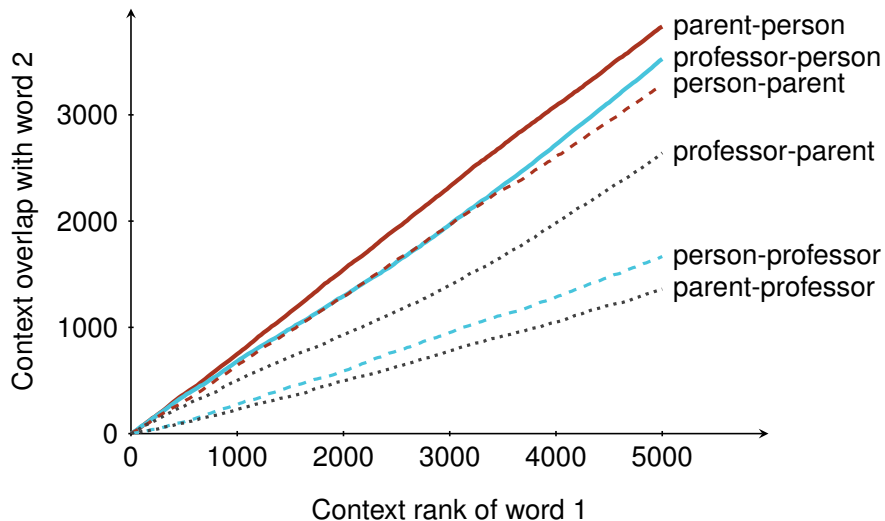
“pointwise mutual information”

parent argcount_n arglist_n arglist_j phane_n specity_n qdisc_n carthy_n
parents-to-be_n non-resident_j step-parent_n tc_n ballons_n
eliza_n symptons_n adoptive_j stepparent_n nonresident_j
home-school_n scabrid_n petiolule_n ...

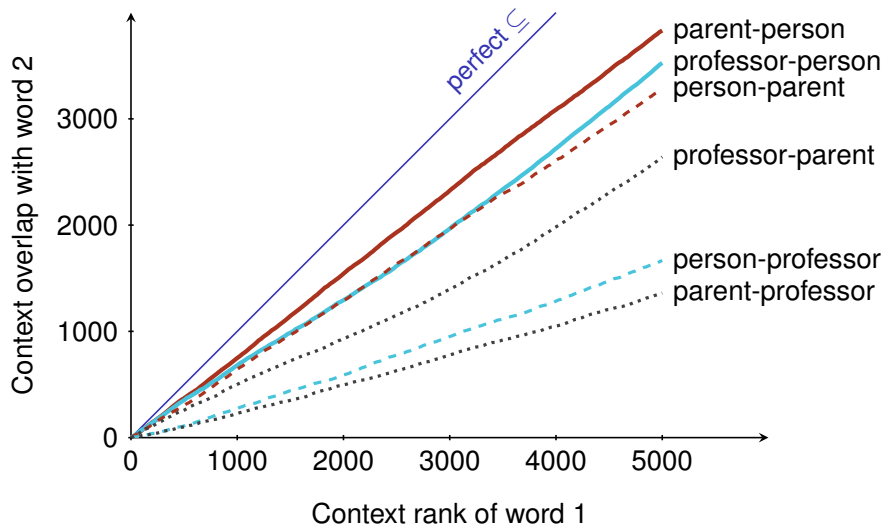
person anglia_n first-mentioned_j unascertained_j enure_v
deposit-taking_j bonis_n iconclass_j cotswolds_n aforesaid_n
haver_v foresaid_j gha_n sub-paragraphs_n enacted_j geest_j
non-medicinal_j sub-paragraph_n intimation_n arrestment_n
incumbrance_n ...

professor william_n extraordinarius_n ordinarius_n francis_n reid_n
emeritus_n emeritus_j derwent_n regius_n laurence_n edward_n
carisoprodol_n adjunct_j winston_n privatdozent_j edward_j
xanax_n tenure_v cialis_n florence_n ...

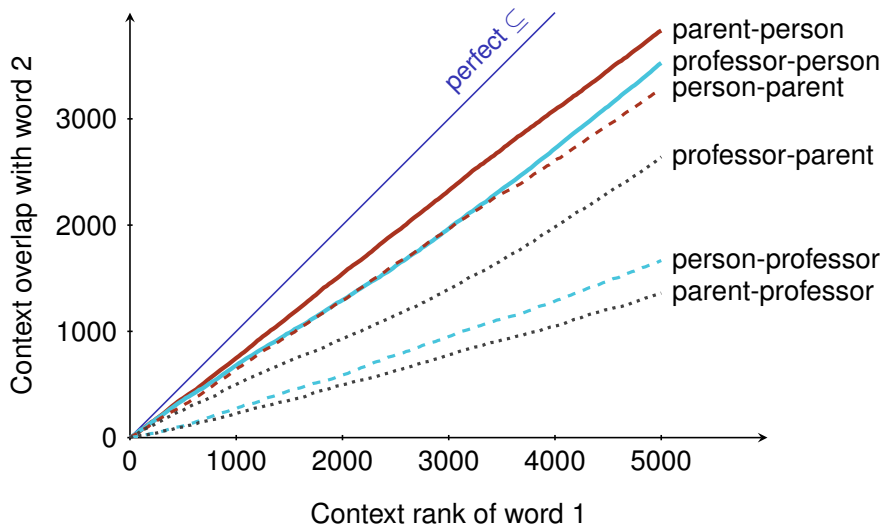
Distributional semantics for entailment among words



Distributional semantics for entailment among words



Distributional semantics for entailment among words



Better: *skew divergence* (Lee), *balAPinc* (Kotlerman et al.), ...

Above the word level

Phrases have corpus distributions too!

N	cat
AN	white cat
QN	every cat

Above the word level

Phrases have corpus distributions too! But **N** \approx **AN** $\not\approx$ **QN**

		Syntactic category
N	cat	N
AN	white cat	N
QN	every cat	QP

Above the word level

Phrases have corpus distributions too! But $\mathbf{N} \approx \mathbf{AN} \not\approx \mathbf{QN}$

		Syntactic category	Semantic type
N	cat	N	$e \rightarrow t$
AN	white cat	N	$e \rightarrow t$
QN	every cat	QP	$(e \rightarrow t) \rightarrow t$

Above the word level

Phrases have corpus distributions too! But $N \approx AN \not\approx QN$

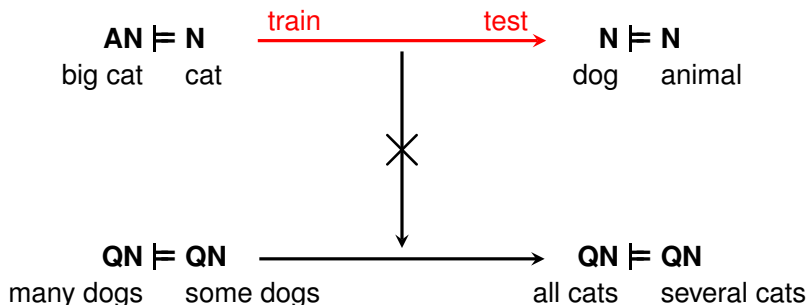
		Syntactic category	Semantic type
N	cat	N	$e \rightarrow t$
AN	white cat	N	$e \rightarrow t$
AAN	big white cat	N	$e \rightarrow t$
QN	every cat	QP	$(e \rightarrow t) \rightarrow t$
QAN	every big cat	QP	$(e \rightarrow t) \rightarrow t$
* AQN	big every cat		
* QQN	some every cat		

Our questions

Entailment among composite phrases rather than nouns?

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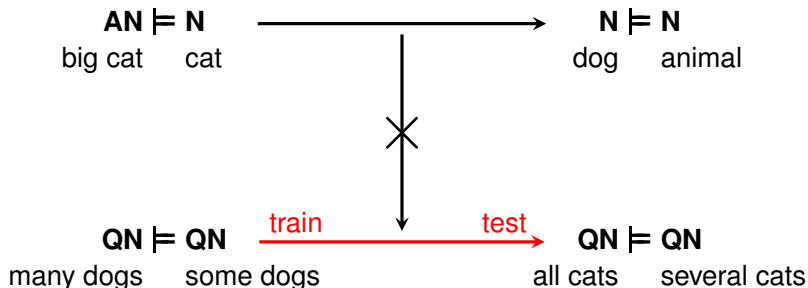


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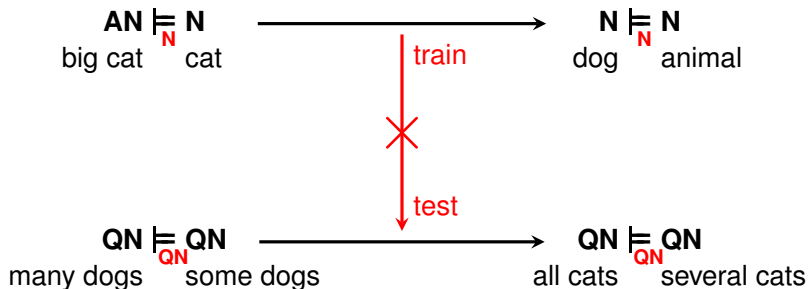


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Our semantic space

BNC, WackyPedia, ukWaC

↓ TreeTagger (Schmid)

lemmatized, POS-tagged tokens (2.8G)

↓ words and phrases in the same sentence

most frequent
A, N, V (27K)

AN
QN
A
Q
N
(48K)

$$\left(\begin{array}{c} \#(c, w) \end{array} \right)$$

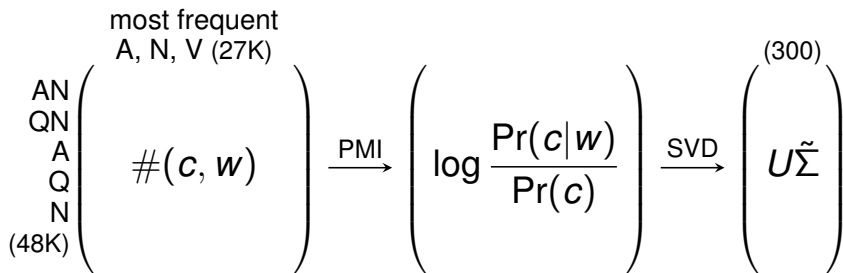
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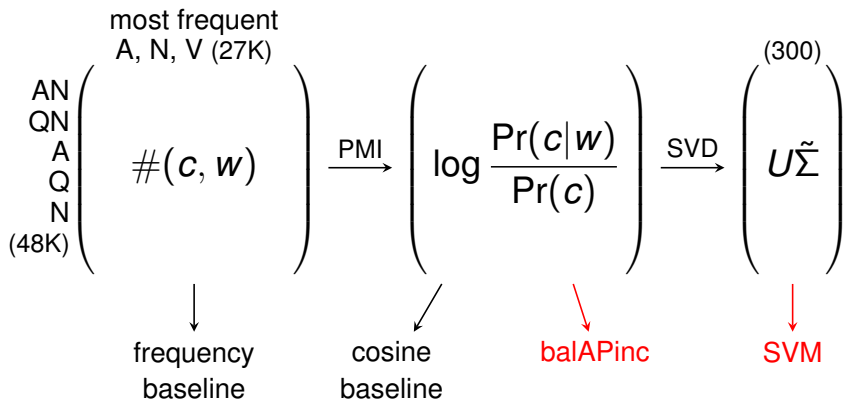
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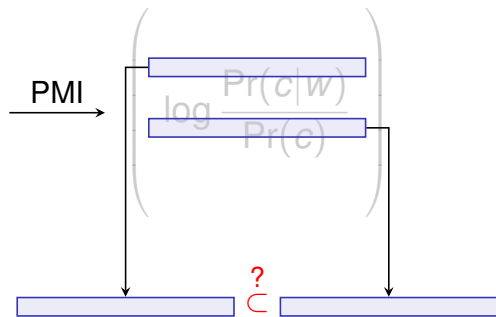
Our entailment classifiers

$$\xrightarrow{\text{PMI}} \left(\log \frac{\Pr(c|w)}{\Pr(c)} \right)$$

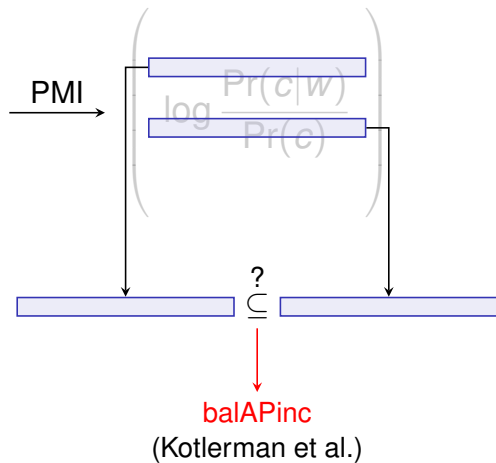
Our entailment classifiers

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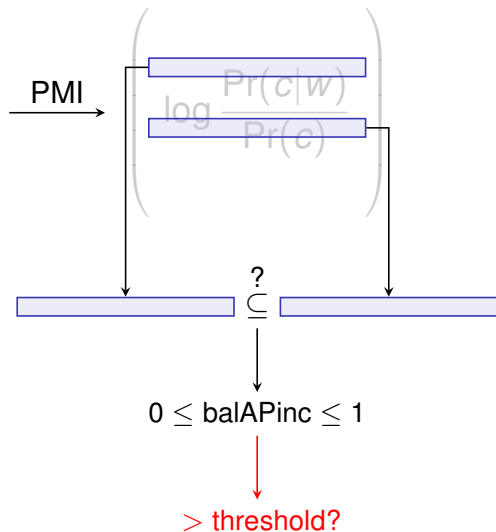
Our entailment classifiers



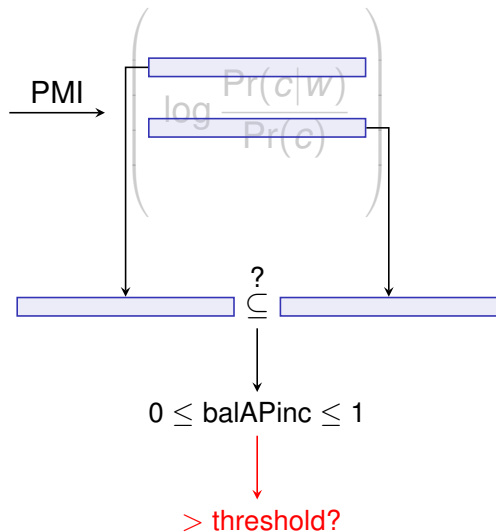
Our entailment classifiers



Our entailment classifiers

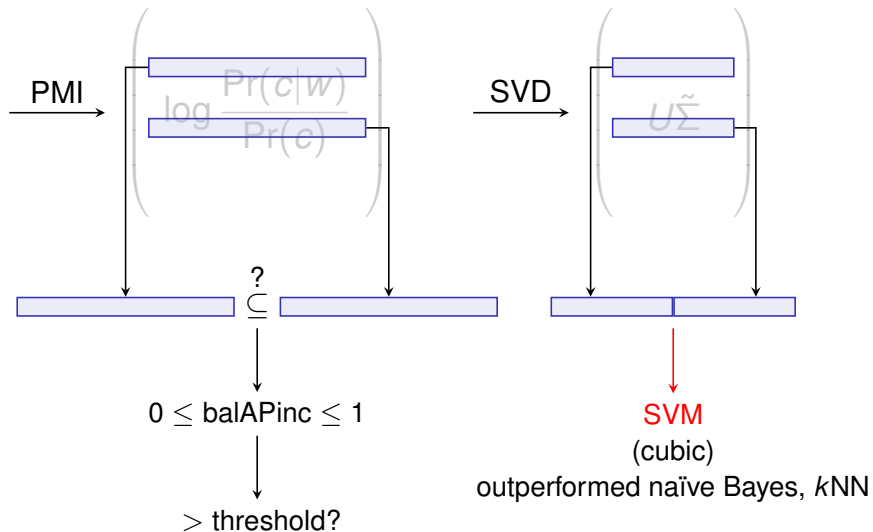


Our entailment classifiers



Train	Test
AN \models N	N \models N
QN \models QN	QN \models QN
AN \models N	QN \models QN

Our entailment classifiers



Our data sets

WordNet



pope \models spiritual_leader

spiritual_leader \models leader

cat \models feline

feline \models carnivore

\vdots

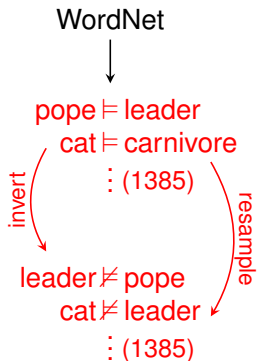
Our data sets

WordNet



pope \models leader
cat \models carnivore
 \vdots (1385)

Our data sets

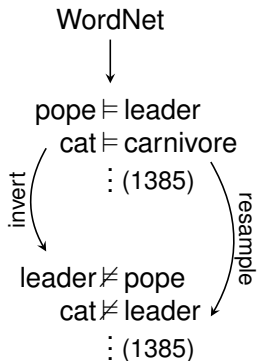


Our data sets

most frequent



big
former
⋮ (300)



Our data sets

most frequent



big

~~former~~

⋮ (256)

WordNet



pope \models leader

cat \models carnivore

⋮ (1385)

invert

leader $\not\models$ pope

cat $\not\models$ leader

⋮ (1385)

resample

Our data sets

most frequent

BLESS

WordNet



big
~~former~~
:
(256)

apple
shirt
:
(200)

pope \models leader
cat \models carnivore
:
(1385)

invert

leader $\not\models$ pope
cat $\not\models$ leader
:
(1385)

resample

big apple \models apple
big shirt \models shirt
:
(1246)

resample

big apple $\not\models$ shirt
big shirt $\not\models$ apple
:
(1244)

Our data sets

most frequent



big
former
⋮ (256)

big apple ⊢ apple
big shirt ⊢ shirt
⋮ (1246)

resample

big apple ≠ shirt
big shirt ≠ apple
⋮ (1244)

BLESS



apple
shirt
⋮ (200)

resample

WordNet



pope ⊢ leader
cat ⊢ carnivore
⋮ (1385)

invert

leader ≠ pope
cat ≠ leader
⋮ (1385)

resample

most frequent



all
both
each
either
every
few
many
most
much
no
several
some
⋮

Our data sets

most frequent



big
~~former~~
⋮ (256)

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WordNet



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cat ⊢ carnivore
⋮ (1385)

invert

leader ≠ pope
cat ≠ leader
⋮ (1385)

resample

most frequent



all ⊢ some
many ⊢ several
⋮ (13)

some ≠ every
both ≠ many
⋮ (17)

Our data sets

most frequent



big
~~former~~
: (256)

big apple \models apple
big shirt \models shirt
: (1246)

resample

big apple $\not\models$ shirt
big shirt $\not\models$ apple
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BLESS



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WordNet



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cat \models carnivore
: (1385)

invert

leader $\not\models$ pope
cat $\not\models$ leader
: (1385)

resample

pope
leader
cat
carnivore
: (6402)

most frequent



all \models some
many \models several
: (13)

some $\not\models$ every
both $\not\models$ many
: (17)

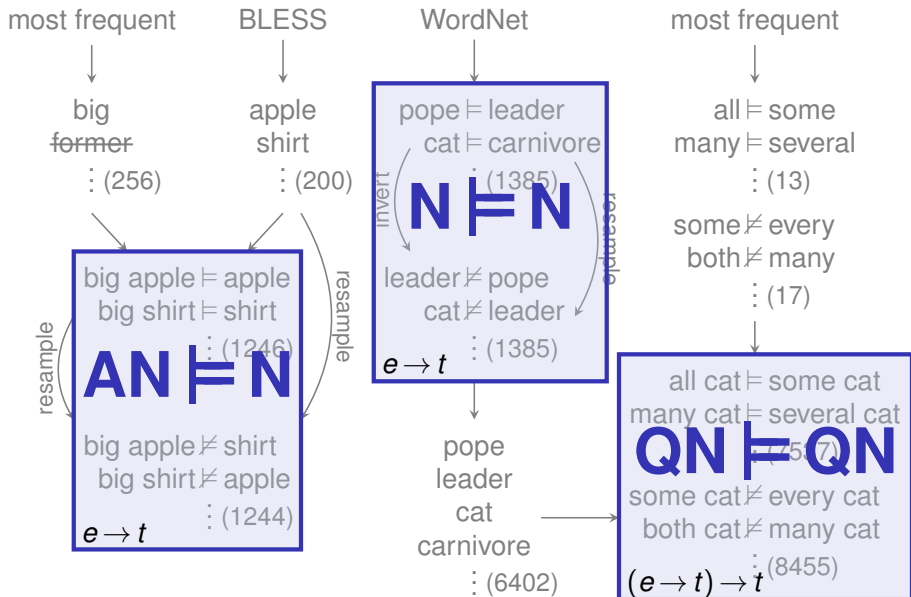


all cat \models some cat
many cat \models several cat
: (7537)

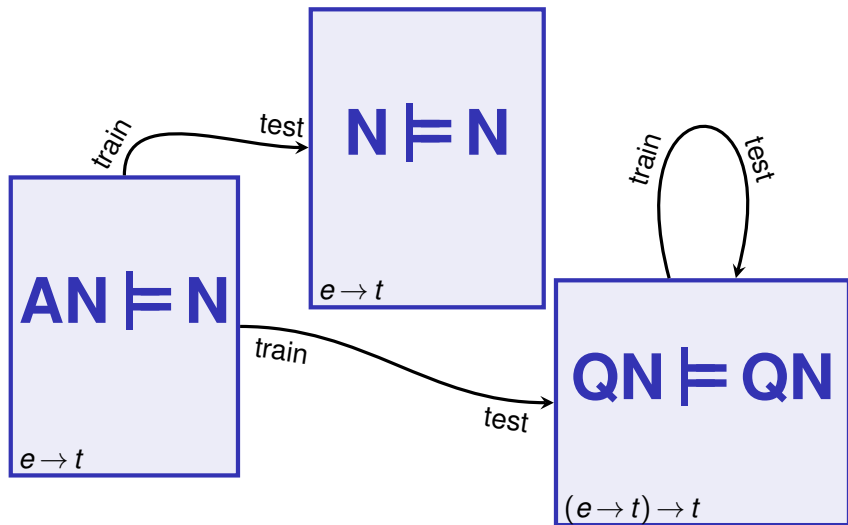
some cat $\not\models$ every cat
both cat $\not\models$ many cat
: (8455)

all cat $\not\models$ every leader
both cat $\not\models$ many leader

Our data sets



Our data sets



Results at noun type

	P	R	F	Accuracy	(95% C.I.)
SVM _{upper}	88.6	88.6	88.5	88.6	(87.3–89.7)
balAPinc _{AN≠N}	65.2	87.5	74.7	70.4	(68.7–72.1)
balAPinc _{upper}	64.4	90.0	75.1	70.1	(68.4–71.8)
SVM _{AN≠N}	69.3	69.3	69.3	69.3	(67.6–71.0)
cos(N ₁ , N ₂)	57.7	57.6	57.5	57.6	(55.8–59.5)
fq(N ₁) < fq(N ₂)	52.1	52.1	51.8	53.3	(51.4–55.2)

Holding out QN data

⋈	all	both	each	either	every	few	many	most	much	no	several	some
all							+	+			+	+
both				+			-	-			-	+
each												+
either		-										
every							+					
few	-						-					
many	-				-			-		-	+	+
most							+					
much												+
no												
several	-				-	-						+
some	-	-			-		-					

Holding out QN data

⋈	all	both	each	either	every	few	many	most	much	no	several	some
all							+	+			+	+
both				+			-	-			-	+
each												+
either		-										
every							+					
few	-						-					
many	-				-			-		-	+	+
most							+					
much												+
no												
several	-				-	-						+
some	-		-		-		-					

pair-out

Holding out QN data

⋈	all	both	each	either	every	few	many	most	much	no	several	some
all							+	+			+	+
both				+			-	-			-	+
each												+
either		-										
every							+					
few	-						-					
many	-						-	-		-	+	+
most							+					
much												+
no												
several	-				-	-						+
some	-	-			-		-					

Diagram annotations:

- A blue cross-shaped highlight covers the 'many' row and 'many' column.
- A red circle highlights the cell at the intersection of 'many' (row) and 'many' (column), with a red line pointing to the text 'pair-out'.
- A blue line points from the text 'quantifier-out' to the rightmost cell in the 'many' row.

Results at quantifier type

	P	R	F	Accuracy	(95% C.I.)
$SVM_{\text{pair-out}}$	76.7	77.0	76.8	78.1	(77.5–78.8)
$SVM_{\text{quantifier-out}}$	70.1	65.3	68.0	71.0	(70.3–71.7)
$SVM_{\text{pair-out}}^Q$	67.9	69.8	68.9	70.2	(69.5–70.9)
$SVM_{\text{quantifier-out}}^Q$	53.3	52.9	53.1	56.0	(55.2–56.8)
$\text{cos}(\text{QN}_1, \text{QN}_2)$	52.9	52.3	52.3	53.1	(52.3–53.9)
$\text{balAPinc}_{\text{AN} \neq \text{N}}$	46.7	5.6	10.0	52.5	(51.7–53.3)
$SVM_{\text{AN} \neq \text{N}}$	2.8	42.9	5.2	52.4	(51.7–53.2)
$\text{fq}(\text{QN}_1) < \text{fq}(\text{QN}_2)$	51.0	47.4	49.1	50.2	(49.4–51.0)
$\text{balAPinc}_{\text{upper}}$	47.1	100	64.1	47.2	(46.4–47.9)

Holding out each quantifier

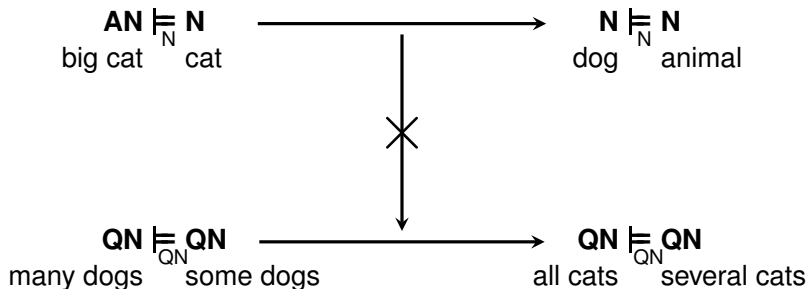
Quantifier	Instances		Correct		
	⊨	⊭	⊨	⊭	
each	656	656	649	637	(98%)
every	460	1322	402	1293	(95%)
much	248	0	216	0	(87%)
all	2949	2641	2011	2494	(81%)
several	1731	1509	1302	1267	(79%)
many	3341	4163	2349	3443	(77%)
few	0	461	0	311	(67%)
most	928	832	549	511	(60%)
some	4062	3145	1780	2190	(55%)
no	0	714	0	380	(53%)
both	636	1404	589	303	(44%)
either	63	63	2	41	(34%)
<i>Total</i>	<i>15074</i>	<i>16910</i>	<i>9849</i>	<i>12870</i>	<i>(71%)</i>

Our questions answered


Entailment among composite phrases rather than nouns? **Yes.**


Entailment among logical words rather than content words? **Yes.**

Different entailment relations at different semantic types? **Yes.**

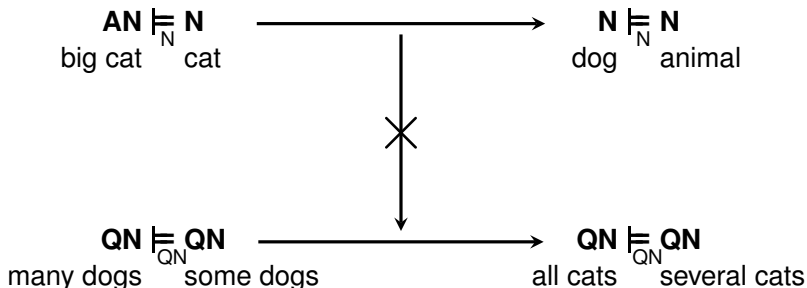


Our questions answered

Entailment among composite phrases rather than nouns? **Yes.**
(Cheap training data!)  Practical import

Entailment among logical words rather than content words? **Yes.**
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(Prediction from formal semantics.)

Ongoing work:

- ▶ How does the SVM work?
- ▶ Missing experiments?
- ▶ How to compose semantic vectors?

Holding out each quantifier pair

Quantifier pair	Instances	Correct	Quantifier pair	Instances	Correct
all \models some	1054	1044 (99%)	some $\not\models$ every	484	481 (99%)
all \models several	557	550 (99%)	several $\not\models$ all	557	553 (99%)
each \models some	656	647 (99%)	several $\not\models$ every	378	375 (99%)
all \models many	873	772 (88%)	some $\not\models$ all	1054	1043 (99%)
much \models some	248	217 (88%)	many $\not\models$ every	460	452 (98%)
every \models many	460	400 (87%)	some $\not\models$ each	656	640 (98%)
many \models some	951	822 (86%)	few $\not\models$ all	157	153 (97%)
all \models most	465	393 (85%)	many $\not\models$ all	873	843 (97%)
several \models some	580	439 (76%)	both $\not\models$ most	369	347 (94%)
both \models some	573	322 (56%)	several $\not\models$ few	143	134 (94%)
many \models several	594	113 (19%)	both $\not\models$ many	541	397 (73%)
most \models many	463	84 (18%)	many $\not\models$ most	463	300 (65%)
both \models either	63	1 (2%)	either $\not\models$ both	63	39 (62%)
			many $\not\models$ no	714	369 (52%)
			some $\not\models$ many	951	468 (49%)
			few $\not\models$ many	161	33 (20%)
			both $\not\models$ several	431	63 (15%)