

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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$AN \models N \quad \longrightarrow \quad N \models N$
big cat cat dog animal

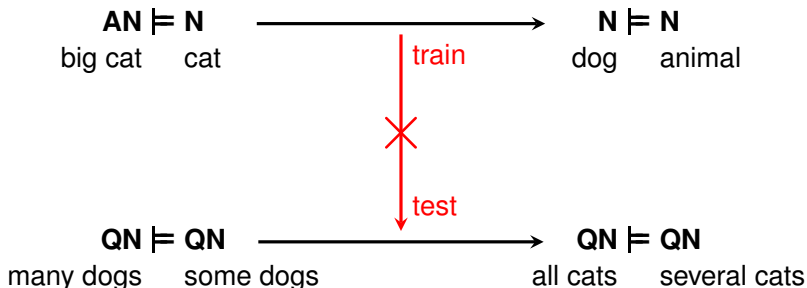
$QN \models QN \xrightarrow{\text{train}} \xrightarrow{\text{test}} QN \models QN$
many dogs some dogs all cats several cats

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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

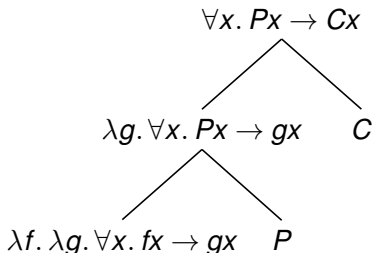
“In order to say what a meaning *is*,
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Truth, entailment

Every person cried. \models Every professor cried.

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

Formal semantics



Approaches to semantics

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and then find something that does that.” —David Lewis

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”

Distributional semantics for entailment among words

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

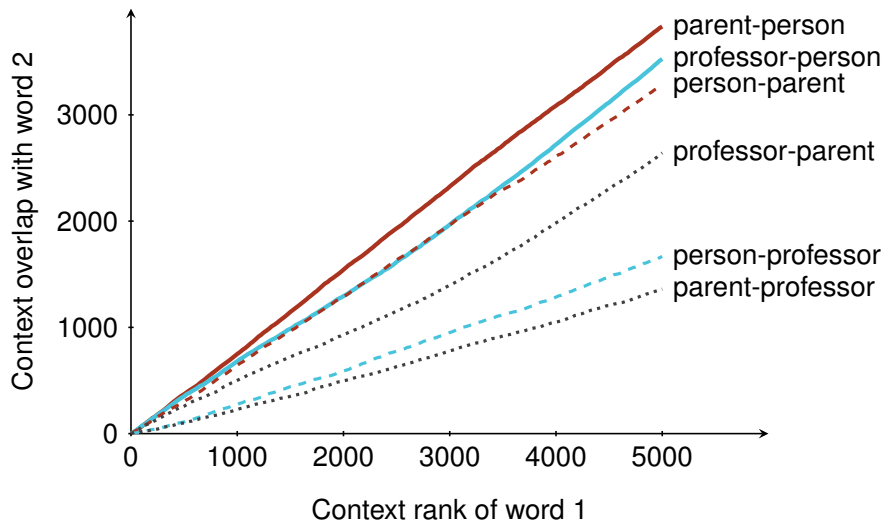
“pointwise mutual information”

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 ...

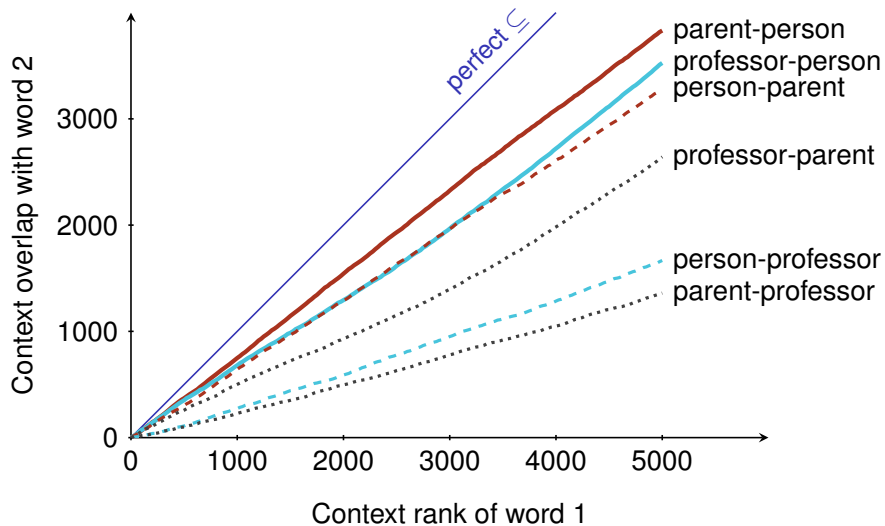
person anglia_n first-mentioned_j unascertained_j enure_v
deposit-taking_j bonis_n iconclass_j cotswolds_n aforesaid_n
haver_v foresaid_j gha_n sub-paragraphs_n enacted_j geest_j
non-medicinal_j sub-paragraph_n intimation_n arrestment_n
incumbrance_n ...

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 ...

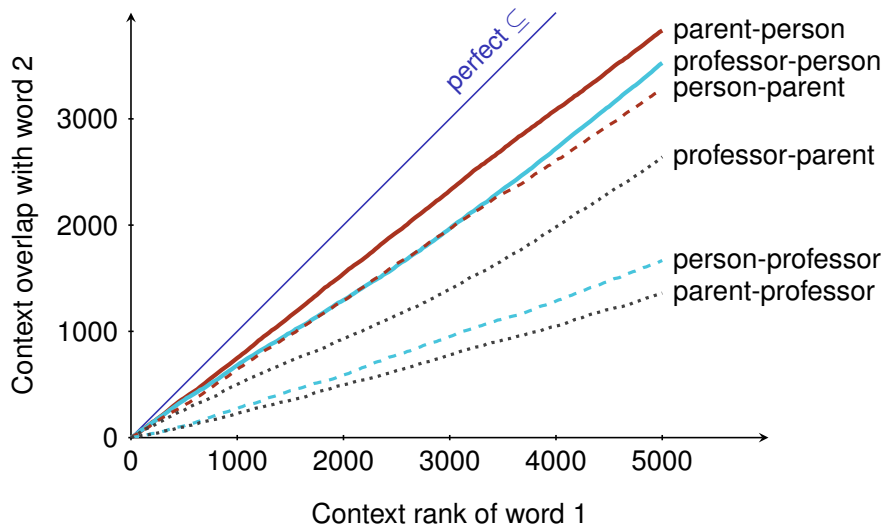
Distributional semantics for entailment among words



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 $N \approx AN \not\approx QN$

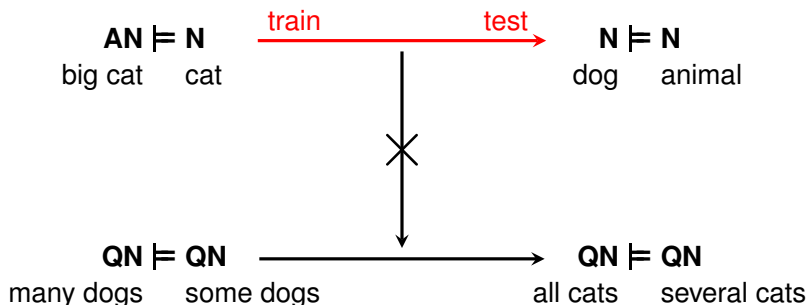
| | | Syntactic category | Semantic type |
|--------------|----------------|--------------------|-----------------------------------|
| N | cat | N | $e \rightarrow t$ |
| AN | white cat | N | $e \rightarrow t$ |
| AAN | big white cat | N | $e \rightarrow t$ |
| QN | every cat | QP | $(e \rightarrow t) \rightarrow t$ |
| 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?

Entailment among logical words rather than content words?

Different entailment relations at different semantic types?

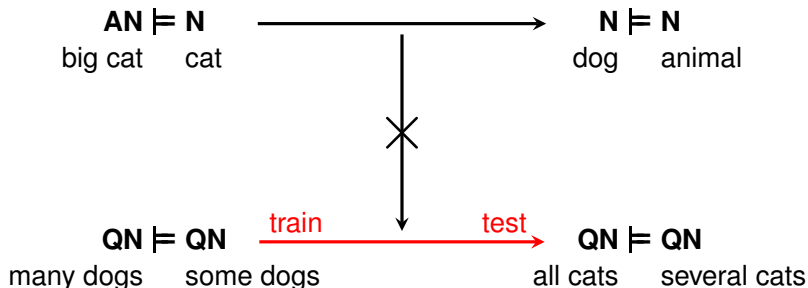


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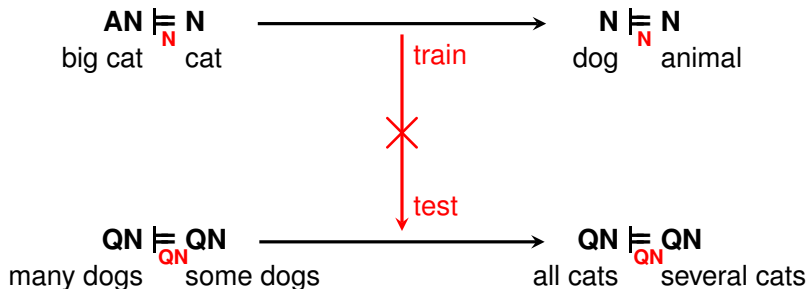


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Our semantic space

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)

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

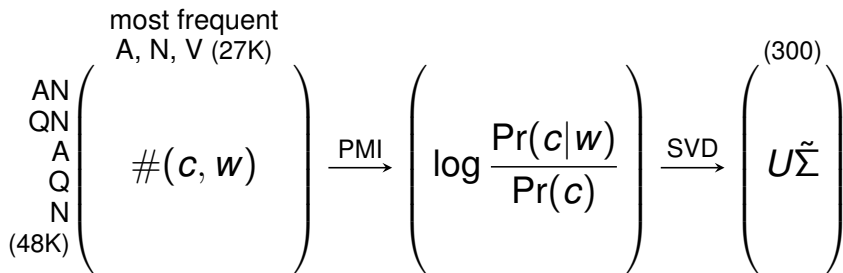
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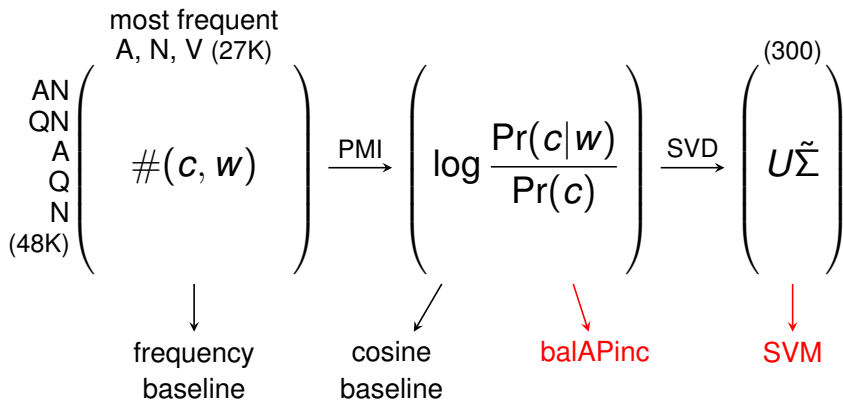
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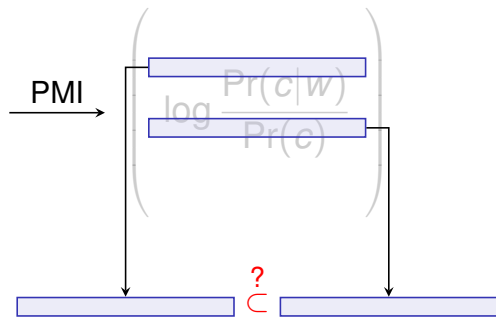
Our entailment classifiers

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

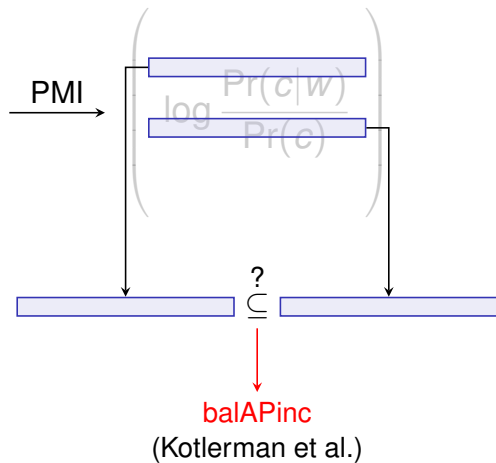
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$$\xrightarrow{\text{PMI}} \left(\begin{array}{c} \log \frac{\Pr(c|w)}{\Pr(c)} \end{array} \right)$$

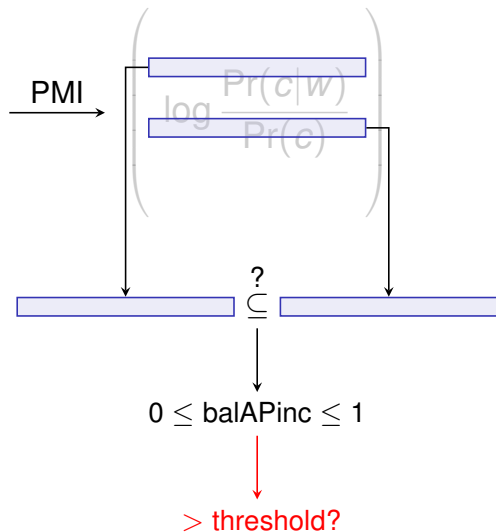
Our entailment classifiers



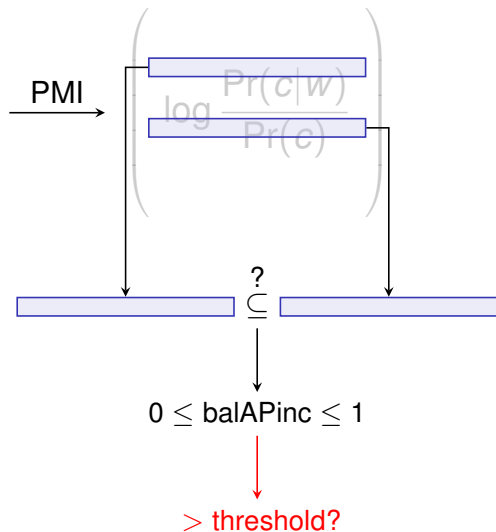
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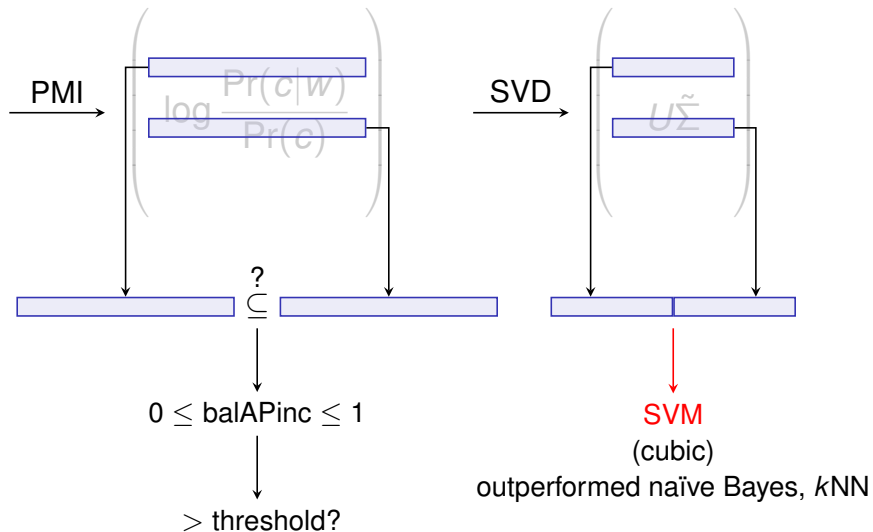


Our entailment classifiers

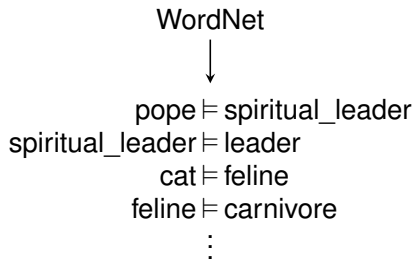


| Train | Test |
|-----------------|-----------------|
| AN \models N | N \models N |
| QN \models QN | QN \models QN |
| AN \models N | QN \models QN |

Our entailment classifiers



Our data sets



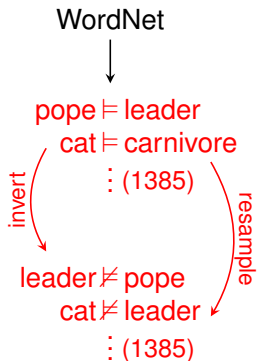
Our data sets

WordNet



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

Our data sets

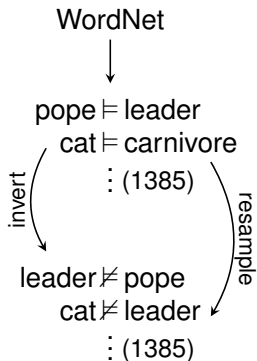


Our data sets

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)

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

resample

invert

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

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)

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

resample

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

BLESS



apple
shirt
: (200)

resample

WordNet



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

invert

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

resample

most frequent



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

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

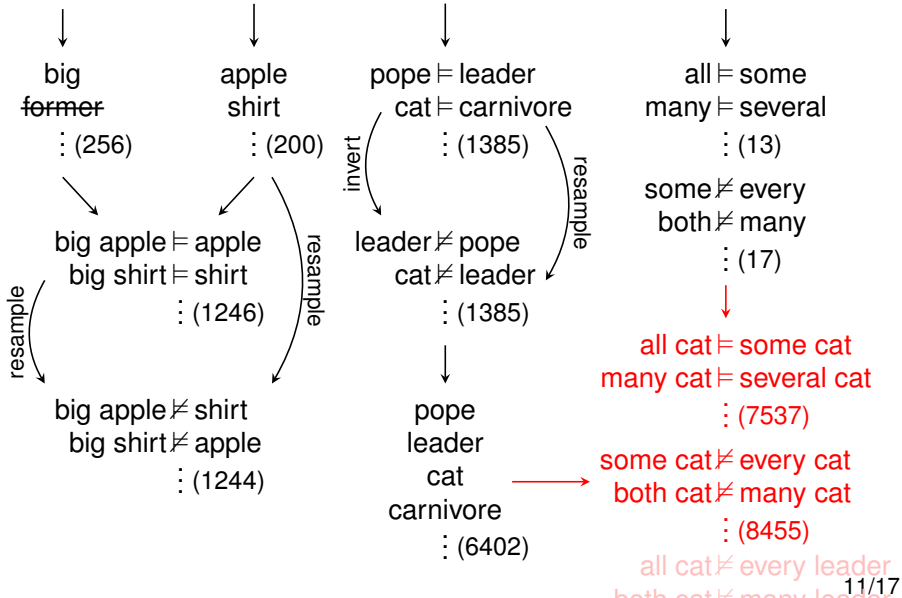
Our data sets

most frequent

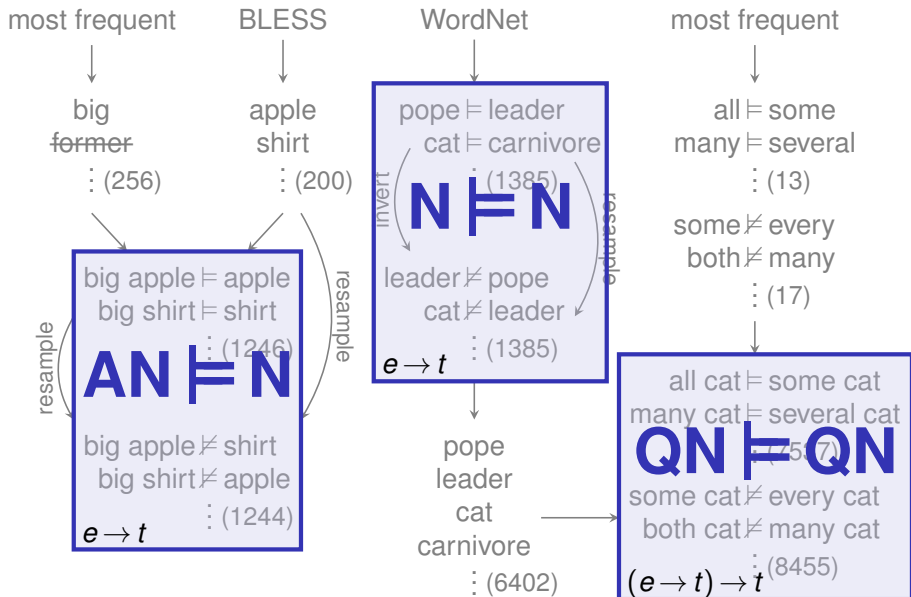
BLESS

WordNet

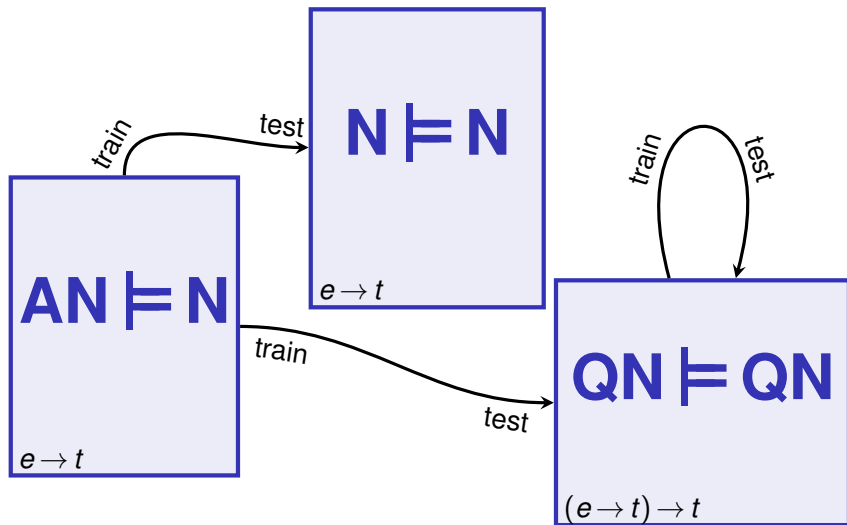
most frequent



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 intersection of the 'many' row and 'many' column.
- A red circle highlights the cell at the intersection of the 'many' row and 'no' column, with a red line pointing to the text 'pair-out'.
- A blue line points from the text 'quantifier-out' to the cell at the intersection of the 'many' row and 'some' column.

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

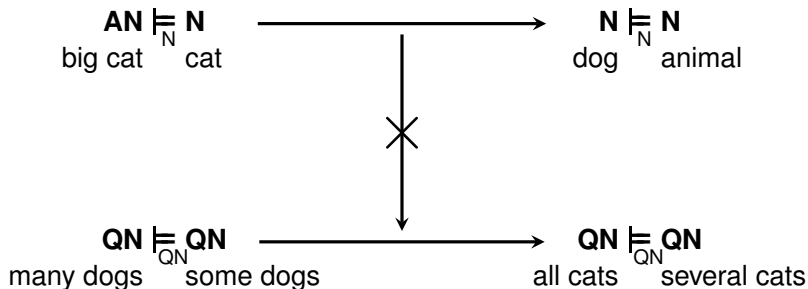
| Quantifier | Instances | | Correct | | |
|--------------|--------------|--------------|-------------|--------------|--------------|
| | ⊨ | ⊭ | ⊨ | ⊭ | |
| each | 656 | 656 | 649 | 637 | (98%) |
| every | 460 | 1322 | 402 | 1293 | (95%) |
| much | 248 | 0 | 216 | 0 | (87%) |
| all | 2949 | 2641 | 2011 | 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.**

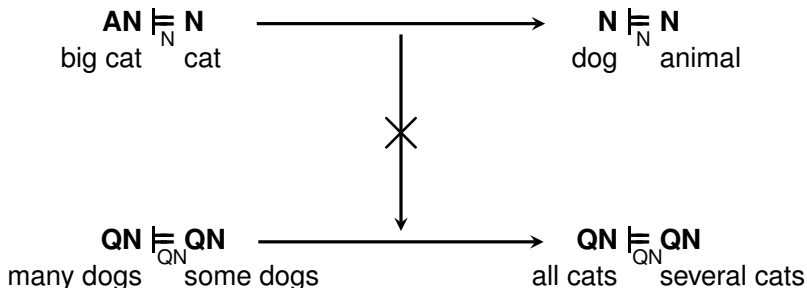


Our questions answered

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

Entailment among logical words rather than content words? **Yes.**
(Part of Recognizing Textual Entailment?)  Practical import

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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%) |