Graded Annotations of Word Meaning in Context

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Outline

Introduction

Alternative Word Meaning Annotations Graded Judgments (Usim and WSsim)

Analyses

Correlation Between Datasets Sense Groupings Usim, Paraphrases and Translations Computational Models

Conclusions



Word Sense Representation and Disambiguation

Some conclusions so far

- what is the right inventory?
- how can we compare different representations?
- how to paraphrases and substitutes relate to sense annotations?
- are we right to assume groupings of word senses?

Manually produced inventories: e.g. WordNet

match has 9 senses in WordNet including:-

- ▶ 1. match, lucifer, friction match (lighter consisting of a thin piece of wood or cardboard tipped with combustible chemical; ignites with friction; "he always carries matches to light his pipe")
- 3. match (a burning piece of wood or cardboard; "if you drop a match in there the whole place will explode")
- ▶ 6. catch, match (a person regarded as a good matrimonial prospect)
- ▶ 8. couple, mates, match (a pair of people who live together; "a married couple from Chicago")
- ▶ 9. match (something that resembles or harmonizes with; "that tie makes a good match with your jacket")

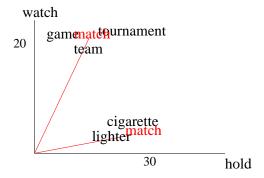


Vector based models

```
watch
20 game tournament
team s4
s1 match

s6 cigarette
lighter s3
30 hold
```

Vector based models



Given a word in context, find the best-fitting "sense" Residents say militants in a station wagon pulled up, doused the building in gasoline, and struck a match.

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match#n#1

Given a word in context, find the best-fitting "sense"

This is at least 26 weeks by the week in which the approved match with the child is made.

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match#n#9

Given a word in context, find the best-fitting "sense"

This is at least 26 weeks by the week in which the approved match with the child is made.

#9 something that resembles or harmonizes with; "that tie makes a good match with your jacket" #8 a pair of people who live together; "a married couple from Chicago"



match#n#9 or possibly match#n#8

What is the right inventory?

Example *child* WordNet

WNs#	gloss
1	a young person
2	a human offspring
3	an immature childish person
4	a member of a clan or tribe

- should we enumerate senses?
- will it help applications?
- how can we test different inventories?

What is the right inventory?

Example *child* WordNet SENSEVAL-2 groups

WNs#	gloss				
1	a young person				
2	a human offspring				
3	an immature childish person				
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Does this methodology have cognitive validity?

- (Kilgarriff, 2006)
 - Word usages often fall between dictionary definitions
 - The distinctions made by lexicographers are not necessarily the ones to make for an application
- (Tuggy, 1993) Word meanings lie on a continuum between ambiguity and vagueness
- (Cruse, 2000) Word meanings don't have discrete boundaries,
 a more complex soft representation is needed

Does this methodology have cognitive validity?

- ► (Hanks, 2000)
 - Computational procedures for distinguishing homographs are desirable and possible, but...
 - they don't get us far enough for text understanding.
 - Checklist theory at best superficial and at worst misleading.
 - Vagueness and redundancy needed for serious natural language processing
- (McCarthy, 2006) Word meanings between others e.g.

Alternative word meaning annotations: datasets

to compare different representations of word meaning in context

- SemEval-2007 Lexical Substitution (LEXSUB)
 (McCarthy and Navigli, 2007)(McCarthy and Navigli, 2009)
- ➤ SemEval-2010 Cross-Lingual Lexical Substitution (CLLS) (Mihalcea et al., 2010)
- ▶ Usage Similarity (Usim) and Graded Word Sense (WSsim) (Erk et al., 2009) and on going . . .

LEXSUB and CLLS

Example: stiff

- 1) Even though it may be able to pump a normal amount of blood out of the ventricles, the <u>stiff</u> heart does not allow as much blood to enter its chambers from the veins.
- 3) One stiff punch would do it.
- 7) In 1968 when originally commissioned to do a cigarstore Indian, he rejected the <u>stiff</u> image of the adorned and phony native and carved "Blue Nose," replica of a Delaware Indian.

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S	LEXSUB substitutes	CLLS translations
1	rigid 4; inelastic 1; firm 1; inflexi-	duro 4; tieso 3; rigido 2; agarro-
	ble 1	tado 1; entumecido 1
3	strong 2; firm 2; good 1; solid 1;	duro 4; definitivo 1; severo 1;
	hard 1	fuerte 1
7	stern 1; formal 1; firm 1; unrelaxed	duro 2; forzado 2; fijo 1; rigido 1;
	1; constrained 1; unnatural 1; un-	acartonado 1; insipido 1
	bending 1	

WSsim and Usim

- new datasets to explore subtler representations of sense
- modelled as psycholinguistic experiment: no right or wrong answer
- use multiple annotators and check consensus
- WSsim (word sense similarity) for a given context of a word, rate every sense in terms of its relevance on a graded scale (1-5)
- ▶ Usim (usage similarity) for a pair of contexts of a word, rate the pair in terms of similarity of use on a graded scale (1-5)

WSsim and Usim: motivations

- compare to existing annotations, paraphrases and translations
- ▶ WSsim
 - explore the extent that multiple senses apply with less bias to annotators
 - explore whether graded annotations are explained by sense groupings
- Usim
 - examine phenomena without a predefined sense inventory

Annotation

- 2 rounds
- all annotators native English speakers
- nouns, verbs, adjectives, adverbs (1st round adverbs only Usim)

Round 1 Erk et al. (2009)

- ▶ 3 annotators for Usim, and 3 for WSsim (1 did both)
- ightharpoonup no particular expertise (ages, undergrad ightarrow early 50s, all women)
- one sentence of context for each target instance
- data released (http://www.katrinerk.com/graded-sense-andusage-annotation)

Round 2

- 8 annotators , all doing all for tasks
- one phd comp linguistics (rest not, but 2 had done round 1)
- ▶ 4 men, 4 women (ages 18-early 50s)
- Usim WSsim, traditional word sense tagging WSbest, lexical substitution SYNbest
 - ▶ group 1: Usim, SYNbest, WSsim, WSbest
 - ▶ group 2: Usim, SYNbest, WSbest, WSsim
- ▶ 2 sentences of context for each instance, an extra sentence either side of that with target
- data to be released on publication (from http://www.dianamccarthy.co.uk/)
- part of Usim-2 released already (Cicling 2011, with R code)

WSsim interface

Sentence #21

4 How can one generate the probability density **function** of an Erlang distribution using Stella?

Rate how close the meaning of the above boldfaced word is to each of the following descriptions:

1=Completely Different, 2=Mostly Different, 3=Similar, 4=Very Similar, 5=Identical

Click for Full Instructions

- \circ 1 $\,\circ$ 2 $\,\circ$ 3 $\,\circ$ 4 $\,\circ$ 5 duty (the actions and activities assigned to or required or expected of a person or group)
- 01 02 03 04 05 utility (what something is used for)
- 01 02 03 04 05 software system (a set sequence of steps, part of larger computer program)
- 01 02 03 04 05 social event (a vaguely specified social event)
- 01 02 03 04 05 social gathering (a formal or official social gathering or ceremony)
- \circ 1 \circ 2 \circ 3 \circ 4 \circ 5 mathematical relation ((mathematics) a mathematical relation such that each element of a given set (the domain of the function) is associated with an element of another set (the range
- of the function)) \circ 1 \circ 2 \circ 3 \circ 4 \circ 5 relation (a relation such that one thing is dependent on another)

-Comment: -

WSsim-2 interface

Sentence 1 - rate how well each of the descriptions reflect the meaning of the underlined word in the se

The British had established a new ruler in Chitral. During the siege, George Robertson had appointed Shuja-ul-Mulk, who was a <u>bright</u> by years old and the youngest surviving son of Aman-ul-Mulk, as the ruler of Chitral. Shuja-ul-Mulk ruled until 1936 and had four wives and concubines, all of whom produced children.

Word sense similarity:

- emitting or reflecting light readily or in large amounts; "the sun was bright and hot"; "a bright sunlit room" \circ 1 \circ 2 \circ 3 \circ 4 \circ 5

undimmed - not made dim or less bright; "undimmed headlights"; "surprisingly the curtain started to rise while the houselights were still undimmed"

promising, hopeful - full or promise; "had a bright future in publishing"; "the scandal threatened an abrupt end to a promising political of a hopeful new singer on Broadway"

vivid, brilliant - having striking color; "bright dress"; "brilliant tapestries"; "a bird with vivid plumage" \circ 1 \circ 2 \circ 3 \circ 4 \circ 5

- splendid; "the bright stars of stage and screen"; "a bright moment in history"; "the bright pageantry of court" \circ 1 \circ 2 \circ 3 \circ 4 \circ 5
- characterized by happiness or gladness; "bright faces"; "all the world seems bright and gay" \circ 1 \circ 2 \circ 3 \circ 4 \circ 5

WSsim Data

- Round 1 (Erk et al., 2009)
 - ▶ 8 lemmas (nouns, verbs and adjectives) 50 sentences each from SemCor (Miller et al., 1993) and SENSEVAL-3 English Lexical Sample (SE-3) (Mihalcea et al., 2004)
 - ▶ 3 lemmas data from LEXSUB 10 sentences each also in Usim
 - 430 sentences
- ▶ Round 2 : 26 lemmas (260 sentences) from LEXSUB,

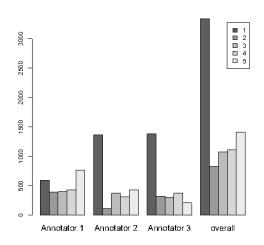
WSsim example

	Senses						
Sentence	1	2	3	4	5	6	7
This question provoked arguments in America about the	1	4	4	2	1	1	3
Norton Anthology of Literature by Women, some of the	4	5	4	2	1	1	4
contents of which were said to have had little value as	1	4	5	1	1	1	1
literature.	•						

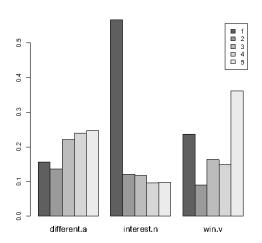
The senses are: 1:statement, 2:controversy, 3:debate, 4:literary argument, 5:parameter, 6:variable, 7:line of reasoning

ITA (average spearmans) Round 1 ho = 0.50 Round 2 ho = 0.60 (ho < 2.2e-16)

WSsim number of times each judgment was used, by annotator and summed over all annotators (R1)



Usim percentage of times each judgment was used for the lemmas *different.a*, *interest.n* and *win.v* summed over 3 annotators (R1)



Percentage of items with multiple senses assigned

 $\textit{Orig}\colon$ in the original SemCor/SE-3 data. WSsim judgment: items with judgments at or above the specified threshold. R1

		WSs	im judg		
Data	Orig.	≥ 3	≥ 4	5	_
WSsim/SemCor	0.0	80.2	57.5	28.3	Overall, 0.3% of
$\mathrm{WSsim}/\mathrm{SE} ext{-}3$	24.0	78.0	58.3	27.1	
All $WSsim$		78.8	57.4	27.7	

tokens in SemCor have multiple labels, and 8% of tokens in SE-3, so the multiple label assignment in our sample is not an underestimate.

WSsim multiple senses having highest response

	Proportion of sentences with		
	multiple senses having highest response		
WSsim-1	0.46		
WSsim-2	0.30		
WSsim-2 group 1	0.36		
WSsim-2 group 2	0.23		

Usim interface

Rate how similar in meaning the two boldfaced words below are:

This is sentence pair number 9

- (1) This more upright position is most easily and affordably achieved through slapping a riser bar on your setup, and only requires you to buy a bar instead of a **bar** and stem.
- (2) For twelve hours Livewire will be broadcasting live from the blue **bar** of Union House at UEA in an attempt to raise as much money as possible for a very worthy cause.
- o 1: Completely different
- 02: Mostly Different
- 03: Similar
- 04: Very Similar
- o 5: Identical
- O Cannot Decide

Click for Full Instructions

Г	Comment:		



Usim-2 interface

Sentence pair 1 - rate how similar in meaning the two underlined words below

- (1) The British had established a new ruler in Chitral. During the siege, George Robertson had appoint 12 years old and the youngest surviving son of Aman-ul-Mulk, as the ruler of Chitral. Shuja-ul-Mulk rul concubines, all of whom produced children.
- (2) It comes into focus more than an inch away from the barrel. The actual field is not much different quite a bit noticeably <u>brighter</u> which is probably the main benefit. The optics are clear and bright, and kellner.

- 1: Completely different
- 02: Mostly Different
- ○3: Similar
- ○4: Very Similar
- 5: Identical
- O Cannot Decide

Usim Data

- ▶ Round 1: (Erk et al., 2009) 3 annotators
 - ▶ 34 lemmas (nouns, verbs, adjectives and adverbs) 10 sentences each from LEXSUB
 - ▶ 340 sentences
- ▶ Round 2 : 26 lemmas (260 sentences). As WSsim round 2 i.e. 8 annotators, extra context.

NB as before in Round 2 we also collected traditional sense annotations (WSbest) and synonyms (SYNbest)

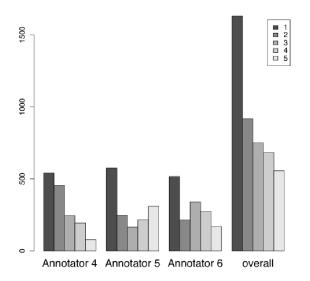
Usim example:

- 1) We study the methods and concepts that each writer uses to defend the cogency of legal, deliberative, or more generally political prudence against explicit or implicit <u>charges</u> that practical thinking is merely a knack or form of cleverness.
- 2) Eleven CIRA members have been convicted of criminal <u>charges</u> and others are awaiting trial.

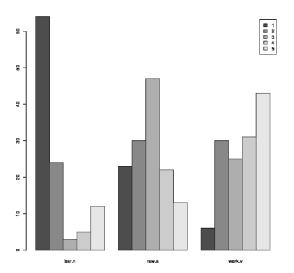
Annotator judgments: 2,3,4

ITA (average spearmans) Round 1 ho = 0.55 Round 2 ho = 0.62 (ho < 2.2e-16)

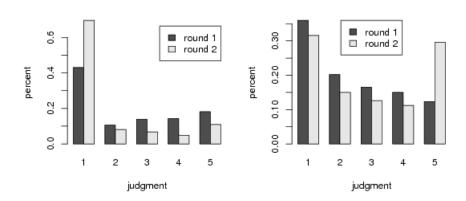
Usim number of times each judgment was used, by annotator and summed over all annotators (R1)



Usim number of times each judgment was used for bar.n, work.v and raw.a (R1)



WSsim and Usim R1 and R2 ratings



The relative frequency of the annotations at each judgment from all annotators

	Judgment							
Exp	1	2	3	4	5			
WSsim-1	0.43	0.106	0.139	0.143	0.181			
WSsim-2	0.696	0.081	0.067	0.048	0.109			
${ m WS}$ sim-2 group 1	0.664	0.099	0.069	0.048	0.12			
WSsim-2 group 2	0.727	0.063	0.065	0.048	0.097			
$\mathrm{U}sim ext{-}1$	0.360	0.202	0.165	0.150	0.123			
Usim-2	0.316	0.150	0.126	0.112	0.296			

Triangular inequality



missed by =

 $max(length(longest) - (length(second\ longest) + length(shortest))0)$

i.e. 0 where the triangular inequality holds.

	% obey	missed by (if missed)
Usim-1	99.2	0.520
Usim-2	100	-

WSbest interface

-Word conce similarity.

Sentence 1 - select the description that best matches the meaning of the und

The British had established a new ruler in Chitral. During the siege, George Robertson had appointed years old and the youngest surviving son of Aman-ul-Mulk, as the ruler of Chitral. Shuja-ul-Mulk ruled concubines, all of whom produced children.

Word School Similarity.
$\hfill \Box$ - emitting or reflecting light readily or in large amounts; "the sun was bright and hot"; "a bright sun was bright
$\hfill \mbox{undimmed}$ - not made dim or less bright; "undimmed headlights"; "surprisingly the curtain started undimmed"
\qed promising, hopeful - full or promise; "had a bright future in publishing"; "the scandal threatened a career"; "a hopeful new singer on Broadway"
$\label{eq:color:problem} \ \ \square \ \ vivid, brilliant - having striking color; "bright dress"; "brilliant tapestries"; "a bird with vivid plumater of the problem of the problem$
$\hfill \Box$ - splendid; "the bright stars of stage and screen"; "a bright moment in history"; "the bright page and screen";
$\hfill\Box$ - characterized by happiness or gladness; "bright faces"; "all the world seems bright and gay"
$\hfill \square$ smart - characterized by quickness and ease in learning; "some children are brighter in one subjection the average"
□ - having lots of light either natural or artificial: "the room was bright and airy": "a stage bright w

↓□▶ ⟨□▶ ⟨□▶ ⟨□▶ □ ♥)

WSbest annotations

	sense selected		Proportion with
	n	у	multiple choice
WSbest	19599	2401	0.13
$\operatorname{WS}best$ group 1	9779	1221	0.15
WSbest group 2	9820	1180	0.11

$$\textit{ITA WSbest} = \sum_{i \in I} \frac{\sum_{\{a_i, a_i'\} \in P_i} \frac{a_i \cap a_i'}{\max(|a_i|, |a_i'|)}}{|P_i| \cdot |I|}$$

ITA 0.574 or 0.626 for items with 1 response from both in pair

SYNbest interface

Sentence 1 - enter a substitute for the underlined word below:

The British had established a new ruler in Chitral. During the siege, George Robertson had appointed years old and the youngest surviving son of Aman-ul-Mulk, as the ruler of Chitral. Shuja-ul-Mulk ruled concubines, all of whom produced children.

-Substitute:-	
Enter substitute : Nil	
Target word is part of phrase:	

PA = 0.261 (LEXSUB 0.278)

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Analyses

Correlation Between Datasets Sense Groupings Usim, Paraphrases and Translations Computational Models

Conclusions



Analyses

- Are these datasets correlated?
- ▶ Do the WSsim responses suggest coarser groupings?
- Usim, paraphrases and translations correlations: can we predict cases of low inter-tagger agreement?

Calculations for Comparing Datasets

- we use mean judgment from all annotators for Usim and WSsim, we use mode for WSbest
- for traditional WSD methodology we assume scores of 1 and 5 (no match vs match)
- Similarity/Distance between Sentence Pairs
 - WSsim we use Euclidean distance between vectors for each sentence
 - SYNbest and LEXSUB use overlap of multiset of substitutes to compare to measures on paired sentences

```
Substitute Overlap: \frac{|multiset\ intersection|}{|larger\ multiset|} e.g. S_1\{game,\ game,\ game,\ tournament\} S_2\{game,\ game,\ competition,\ tournament\}=\frac{3}{4}
```

Correlation of WSsim with traditional methodology

	Original Gold Standard				
Exp	SemCor	SE-3			
$\overline{\mathrm{WS}}$ sim-1 Ann1 $ ho$	0.234	0.346			
$ ext{WS}$ sim-1 Ann2 $ ho$	0.448	0.449			
$ ext{WS}$ sim-1 Ann3 $ ho$	0.390	0.338			
WSsim-1 Average Ind $ ho$	0.357	0.378			
$ ext{WS}$ sim- 1 mean $ ho$	0.426	0.419			

Correlation Between Datasets Sense Groupings Usim, Paraphrases and Translations

Computational Models

Correlation between datasets

tasks	Spearman's $ ho$
Usim-1 LEXSUB	0.590
Usim-2 SYNbest	0.764
WSsim-2 SYNbest	-0.749
WSsim-1 SemCor	0.426
$WSsim-1~\mathrm{SE-3}$	0.419
WSsim-2 wsbest	0.483
Usim-2 WSsim-2	-0.816

Correlating senses: WSsim of two senses of account

WordNet sense	Sentence									
	1	2	3	4	5	6	7	8	9	10
account%1:10:00::	1.0	2.3	1.1	4.3	1.1	1.0	1.1	1.1	1.1	4.3
account%1.10:04::	1.5	3.0	1.3	2.9	1.5	1.5	1.6	1.0	1.4	3.9

Percentage of sense pairs that were significantly positively (pos) or negatively (neg) correlated

	<i>p</i> <	0.05	<i>p</i> <	0.01
	pos	neg	pos	neg
Rd. 1	30.3	22.2	21.1	16.8
Rd. 2	14.3	11.1	8.0	4.6

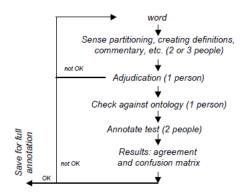
Percentage of sentences with two uncorrelated or negatively correlated senses have judgments above a threshold

Lemmas in WSsim having coarse grained mappings

		I	R2	
lemma	ON (Hovy et al., 2006)	EAW (Navigli et al., 2007)	ON	EAW
account.n				
add.v	\checkmark			
ask.v	\checkmark	\checkmark		
call.v			$\sqrt{}$	$\sqrt{}$
coach.n		,		
different.a		\checkmark	,	,
dismiss.v			$\sqrt{}$	\checkmark
fire.v			$\sqrt{}$	
fix.v			$\sqrt{}$,
hold.v				$\sqrt{}$
lead.n				$\sqrt{}$
new.a	,		,	\checkmark
order.v	√	/	V	
paper.n rich.a		V		/
ricn.a shed.n			/	V
suffer.v			V /	/
win.v	/	/	V	V
WIII.V	V	V		

Ontonotes Annotation Procedure

This figure is from Hovy et al. (2006)



WordNet 2.1 senses of the noun account, and groups in OntoNotes (ON) and EAW (ODE)

WordNet	ON	EAW
key	group	group
account%1:26:00::	1.1	5
account%1:10:05::	1.2	2
account%1:10:04::	1.2	2
account%1:10:00::	1.3	2
	key account%1:26:00:: account%1:10:05:: account%1:10:04::	key group account%1:26:00:: 1.1 account%1:10:05:: 1.2 account%1:10:04:: 1.2

Sentences with positive judgments for senses in different coarse groupings

		Onto	Notes			EA'	W	
J.	Rd. 1 Rd. 2		Rd. 1		Rd. 2			
≥ 3	28%	(42)	52%	(52)	78%	(157) (82)	62%	(50)
≥ 4	13%	(19)	16%	(16)	41%	(82)	22%	(18)
		(5)	3%	(3)	8%	(17)	6%	(5)

Sentences that have widely different judgments for pairs of senses in the same coarse grouping

		OntoNotes				EAW			
J1	J2	Rd	. 1	Rd	. 2	Rd	. 1	Rd	. 2
<u>≤ 2</u>	≥ 4	35%	(52)	30%	(30)	20%	(39)	60%	(48)
≤ 2	5	11%	(16)	4%	(4)	2%	(4)	15%	(12)

Average Usim for R2 where WSbest annotations suggested the same or different coarse grouping

	ON		EAW	
	same	different	same	different
	4.0	1.9	4.1	2.0
	by lemma			
account.n	4.0	1.6	4.0	1.5
call.v	4.3	1.4	4.3	1.4
coach.n	4.6	2.3	-	-
dismiss.v	3.8	2.6	3.8	2.6
fire.v	4.6	1.2	-	-
fix.v	4.2	1.1	-	-
hold.v	4.5	2.0	3.8	1.9
lead.v	-	-	2.9	1.5
new.a	-	-	4.6	4.6
order.v	4.3	1.7	-	-
rich.a	-	-	4.6	2.0
shed.v	2.9	3.3	-	-
suffer.v	4.2	-	4.2	-

Paraphrases, translations and Usim analysis

- ▶ data common to CLLS, Usim-1 or -2 and LEXSUB
- ▶ 32 lemmas (Usim-1) + 24 lemmas (Usim-2) (4 lemmas in both)
- Usim take the mean judgments (as above)
- overlap in paraphrases and translations (as above)

Correlation between datasets

datasets	ρ
LEXSUB-CLLS	0.519
${\tt LEXSUB-Usim-1}$	0.576
${\tt LEXSUB-Usim-2}$	0.724
${ m CLLS-Usim-1}$	0.531
CLLS-Usim-2	0.624

Correlation between datasets . . . by lemma

	LEXSUB	LEXSUB	CLLS	Usim	Usim
lemma	CLLS	Usim	Usim	MID	IAA
account.n	0.322	0.524	0.488	0.389	0.66
bar.n	0.583	0.624	0.624	0.296	0.35
bright.a	0.402	0.579	0.137	0.553	0.53
call.v	0.708	0.846	0.698	0.178	0.65

Correlation between datasets . . . by lemma

LEXSUB	LEXSUB	CLLS	Usim	Usim
CLLS	Usim	Usim	rev MID	IAA
throw.v	lead.n	new.a	fresh.a	new.a
neat.a	hard.r	throw.v	raw.a	function.n
work.v	new.a	work.v	strong.a	fresh.a
strong.a	put.v	hard.r	special.a	investigator.n
dismiss.v	fire.v	rude.a	post.n	severely.r
coach.n	rich.a	coach.n	call.v	flat.a
fire.v	execution.n	fire.v	fire.v	fire.v

Correlation between datasets . . . by lemma

LEXSUB	LEXSUB	CLLS	Usim	Usim
CLLS	Usim	Usim	rev MID	IAA
throw.v	lead.n	new.a	fresh.a	new.a
neat.a	hard.r	throw.v	raw.a	function.n
work.v	new.a	work.v	strong.a	fresh.a
strong.a	put.v	hard.r	special.a	investigator.n
dismiss.v	fire.v	rude.a	post.n	severely.r
coach.n	rich.a	coach.n	call.v	flat.a
fire.v	execution.n	fire.v	fire.v	fire.v
0.424	0.528	0.674	-0.486	

WSsim Computational Models: motivations

- could classic models be used to predict graded ratings?
- would vector space models outperform these if provided with training data to partition senses?

Preliminary Modelling of WSsim

- Gold standard provides vector of ratings, one for each sense
- lacktriangle mapped judgments 1-5 ightarrow 0-1
- ► Traditional vs Prototype models
- experiment with WSsim-1 lemmas in SemCor and SENSEVAL

Lemmas in this Study

lemma	#	# traii	ning
(PoS)	senses	SemCor	SE-3
add (v)	6	171	238
argument (n)	7	14	195
ask (v)	7	386	236
different (a)	5	106	73
important (a)	5	125	11
interest (n)	7	111	160
paper (n)	7	46	207
win (v)	4	88	53
total training s	entences	1047	1173

Models

- ► Classic Binary (one classifier per sense)
- Max Entropy http://maxent.sourceforge.net/ (n-ary slightly worse)
- 2 models:
 - best (traditional 0 vs 1)
 - conf (confidence used as rating)

Models: feature representation

feature representation of a sentence. e.g. features for add in BNC occurrence For sweet-sour sauce, cook onion in oil until soft. Add remaining ingredients and bring to a boil.

Cx/2 (Cx/50): context of size 2 (size 50) either side of the target. Ch: children of target.

Cx/2 until, IN, soft, JJ, remaining, VBG, ingredient, NNS

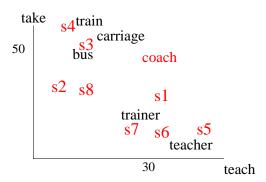
Cx/50 for, IN, sweet-sour, NN, sauce, NN, ..., to, TO, a, DT, boil, NN

Ch OA, OA/ingredient/NNS

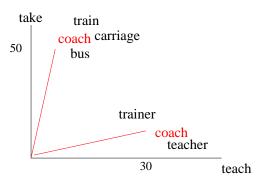
Models: traditional

- Use traditional best fitting training data to obtain probabilistic
 WSD models
 - ▶ Best: best fitting senses
 - ► Conf: probability over senses

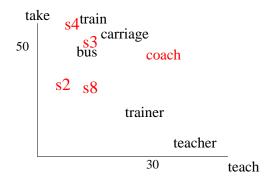
Use vector space models which take best fitting training data Instead of:



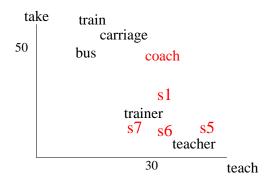
Use vector space models which take best fitting training data Instead of:



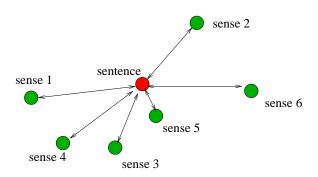
Use vector space models which take best fitting training data



Use vector space models which take best fitting training data



- use training data to create prototypes
- ▶ the DV package, http://www.nlpado.de/~sebastian/dv.html, to compute the vector space.
- one prototype per sense
- same feature representation of a sentence as traditional models
- centroid of vectors for sense (not using 'negative' evidence for different senses)
- classify an occurrence by distance to each sense



- ▶ *Prototype* first order, counts words in sentence
- ▶ Prototype-2 second order for each sentence
 - compute vector for each word
 - sentence vector is centroid of word vectors
- prototype-n prototype-2n normalised judgments for each sentence (assigned / sum for all senses for that item)

Correlation between Gold-Standard and Model

```
lemma: for each lemma \ell \in L, compute correlation between
         G|_{lemma=\ell} and A|_{lemma=\ell}
```

sense: for each lemma ℓ and each sense number $i \in S_{\ell}$. compute correlation between $G|_{Iemma=\ell.senseno=i}$ and $A|_{lemma=\ell.senseno=i}$

token: for each lemma ℓ and sentence number $t \in T$. compute correlation between $G|_{lemma=\ell, sentence=t}$ and

 $A|_{lemma=\ell.sentence=t}$

Jenson Shannon divergence

Symmetric version of kullback-Leibler divergence of probabilities

$$JS(p,q) = \frac{1}{2} (D(p||\frac{p+q}{2}) + D(q||\frac{p+q}{2}))$$

Compare distributions given lemma and sentence

Graded precision and recall

$$P_{\ell} = \frac{\sum_{i \in S_{\ell}, t \in T} \mathsf{min}(\mathsf{gold}_{\ell, i, t}, \mathsf{assigned}_{\ell, i, t})}{\sum_{i \in S_{\ell}, t \in T} \mathsf{assigned}_{\ell, i, t}}$$

and

$$R_{\ell} = \frac{\sum_{i \in S_{\ell}, t \in T} \min(\text{gold}_{\ell, i, t}, \text{assigned}_{\ell, i, t})}{\sum_{i \in S_{\ell}, t \in T} \text{gold}_{\ell, i, t}}$$

- macro averaged by lemma
- precision decrease if model overshoots
- recall decreases as model undershoots
- classical precision and recall if data is categorial.

Experimental set up

- training:
 - SemCor (minus WSsim)
 - ► SE-3 (minus WSsim)
- human ceiling : evaluate performance of one annotator against other two
- baseline: most frequent sense from corpus

Human ceiling: one annotator vs. average of the other two annotators

Avg: average annotator performance

	lemma	sense	token				
Ann	ρ	ρ	ho	J/S	Р	R	F
	0.517						
Ann.2	0.587	0.403	0.612	0.153	75.5	62.4	68.3
Ann.3	0.528	0.41	0.51	0.165	82.4	52.3	64.0
Avg	0.544	0.407	0.535	0.149	69.5	67.4	65.5

Evaluation: computational models, and baseline.

Model	Lρ	s $ ho$	t $ ho$	J/S	Р	R	F
best	0.267	0.053	0.28	0.39	58.7	25.5	35.5
conf	0.396	0.177	0.401	0.164	81.8	37.1	51.0
Prototype	0.245	0.053	0.396	0.173	58.4	78.3	66.9
Prototype/2	0.292	0.086	0.478	0.164	68.2	63.3	65.7
Prototype/N	0.396	0.137	0.396	0.173	82.2	29.9	43.9
Prototype/2N	0.465	0.168	0.478	0.164	82.6	30.9	45.0
baseline	0.338	0.0	0.355	0.167	79.9	34.5	48.2

Average judgment for individual annotators (transformed) and average rating for models

Ann.	avg	Model	avg
Ann.1	0.540	WSD/single	0.163
Ann.2	0.345	WSD/conf	0.173
Ann.3	0.285	Prototype	0.558
		Prototype/N	0.143
		Prototype/2	0.375
		Prototype/2N	0.143
		baseline	0.167

Computational Modelling of Usim

- Contrast vector space models with WordNet
- Vector space model using DV package, http://www.nlpado.de/~sebastian/dv.html
 - minipar parses of BNC
 - frequency, relative frequency, pmi
 - centroid or best (closest vector of words in sentence to target)
 - ightharpoonup correlation with average judgement best higher correlation some significance but ho really small

Computational Modelling of Usim

- WordNet: lesk
- all words (max WordNet similarity in two sentences)
- best (WordNet similarity between 2 words that are closest to target
- Results show no correlation or wrong direction

Summary

- Word meaning annotations using substitutes, translations, graded sense annotations and similarity judgments
- Annotations reflect underlying meanings in context and allow relationships between usages
- WSsim annotations indicate groupings are not straightforward for all lemmas
- Usim judgments alongside traditional WSD annotations might highlight difficult lemmas

. . .



Summary contd.

- Annotations of similarity of usage show highly significant correlation to substitutes and translations
- Correlation is not evident for all lemmas
- Correlation between these annotations by lemma itself correlates with Usim inter-tagger agreement
- Proportion of Usim mid scores by lemma is a useful indicator of low inter-tagger agreement and issues with separability of senses

Ongoing and future work

- Datasets available for evaluating different representations of meaning
- ...particularly fully unsupervised
- Analysis of the extent that paraphrases and translations can be clustered

Thank You

and thanks also to . . .
Collaboration with Roberto Navigli
and Katrin Erk and Nick Gaylord
and Rada Mihalcea, Ravi Sinha
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- LEXSUB task web site: http://www.dianamccarthy.co.uk/task10index.html
- CLLS web site: http://lit.csci.unt.edu/index.php/Semeval_2010
- ► Usim and WSsim from websites of Katrin Erk and Diana McCarthy

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