Towards Universal Semantic Tagging

Lasha Abzianidze (joint work with Johan Bos) 29.05.2018





From *lexical* semantics to phrasal semantics

Semantic lexicon is usually large

From *lexical* semantics to phrasal semantics

Semantic lexicon is usually large

Which lexical semantics to assign to word tokens?

From *lexical* semantics to phrasal semantics

Semantic lexicon is usually large

Which lexical semantics to assign to word tokens?

- <u>07/1937</u> I have gone to the cinema
- 00/1564 I have a big dog
- 00/2206 I have to warn him

From *lexical* semantics to phrasal semantics

Semantic lexicon is usually large

Which lexical semantics to assign to word tokens?

- o <u>07/1937</u> I have gone to the cinema
- 00/1564 I have a big dog
- 00/2206 I have to warn him

Can POS tags help?

From *lexical* semantics to phrasal semantics

Semantic lexicon is usually large

Which lexical semantics to assign to word tokens?

- o <u>07/1937</u> I have gone to the cinema
- 00/1564 | have a big dog
- 00/2206 I have to warn him

Can POS tags help? NO as all the three gets VBP

More examples

- He himself^{PRP} tried it, Tom cut himself^{PRP} while shaving
- o and cc, or cc, but cc
- o ... to^{TO} write ..., ... to^{TO} cinema ...
- does not like any^{DT} X. Give me any^{DT} X
- a(n)/every/no/the/some/each/that/these/(n)either...^{DT}
- iII^{JJ} / skillful^{JJ} / fake^{JJ} professor
- Google, New York; Ann, Bill and Mary; Ann, a director,...

Outline

- Groningen/Parallel Meaning bank
- UNIversal SEmantic Tagset
- Results & Challenges
- Conclusion

Formal compositional semantics in Parallel Meaning Bank

- Heavy lexical units: DRSs
- Few combining rules: Rules of CCG
- λ-calculus for computation: λ-DRS

```
male.n.02(x1)
leave.v.01(e1)
  Time(e1, t1)
  Theme(e1, x1)
time.n.08(t1)
  t1 X t2
  t1 < now
measure.n.02(t2)
  t2 X now
  Unit(t2, day)
  Theme(t2, 3)
```

Formal compositional semantics in Parallel Meaning Bank

- Heavy lexical units: DRSs
- Few combining rules: Rules of CCG
- λ-calculus for computation: λ-DRS

```
| left | λν1.λν2. (ν1 @ λν3. ( e1 t1 | ; (ν2 @ e1) )) | leave(e1) | Time(e1, t1) | Theme(e1, v3) | time(t1) | t1 < now
```

```
male.n.02(x1)
leave.v.01(e1)
  Time(e1, t1)
  Theme(e1, x1)
time.n.08(t1)
  t1 X t2
  t1 < now
measure.n.02(t2)
  t2 X now
  Unit(t2, day)
  Theme(t2, 3)
```

Formal compositional semantics in

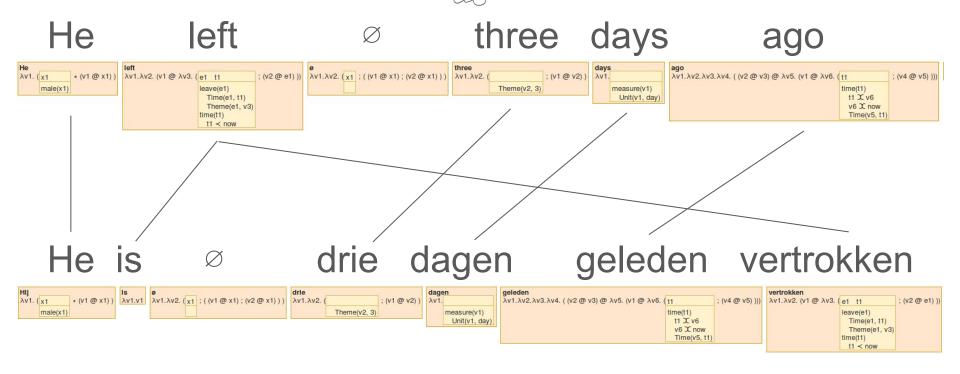
Parallel Meaning Bank

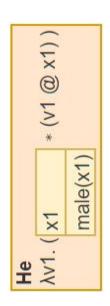
- Heavy lexical units: DRSs
- Few combining rules: Rules of CCG
- λ-calculus for computation: λ-DRS

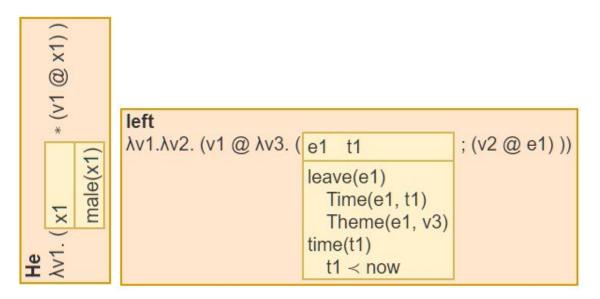
male.n.02(x1)
leave.v.01(e1)
 Time(e1, t1)
 Theme(e1, x1)
time.n.08(t1)

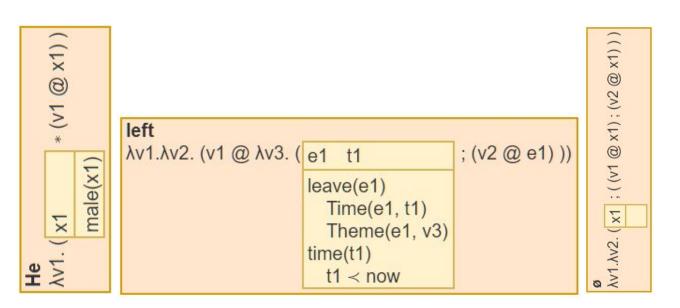
Compositionality

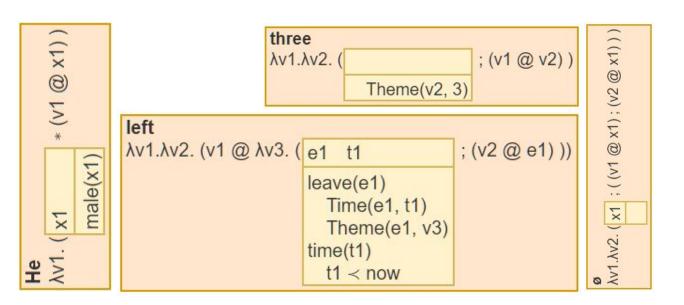
Projection

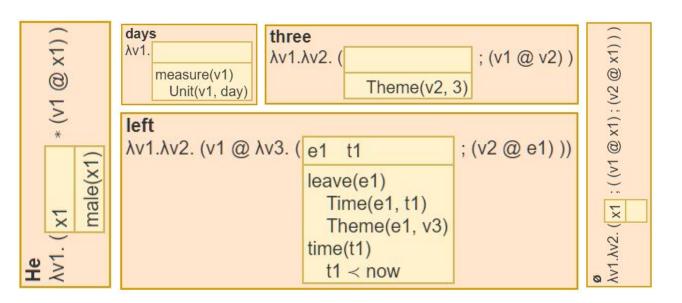


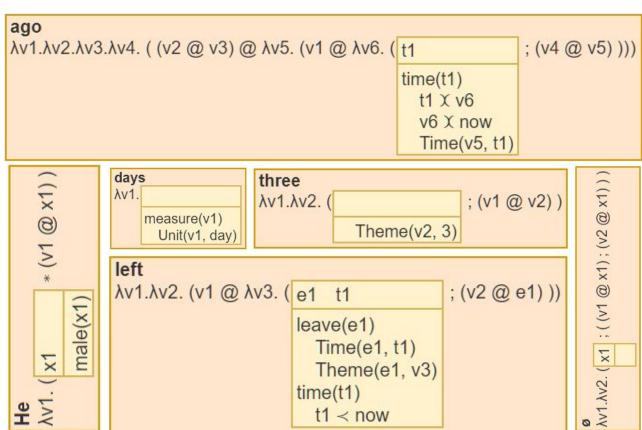


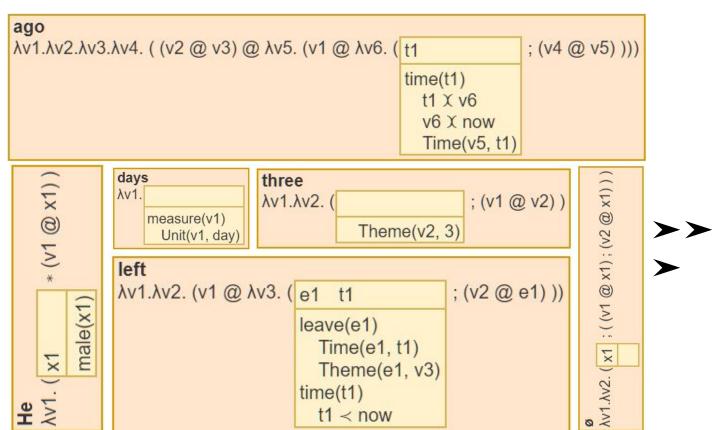


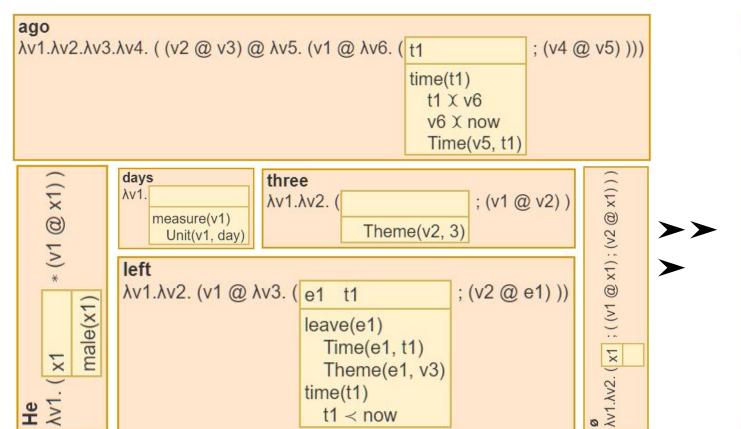




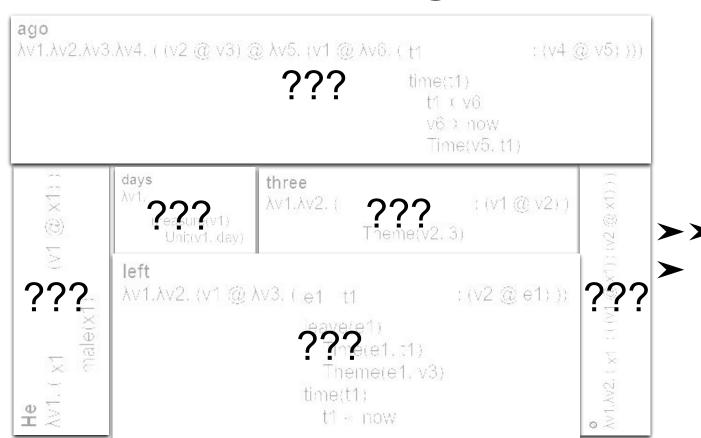








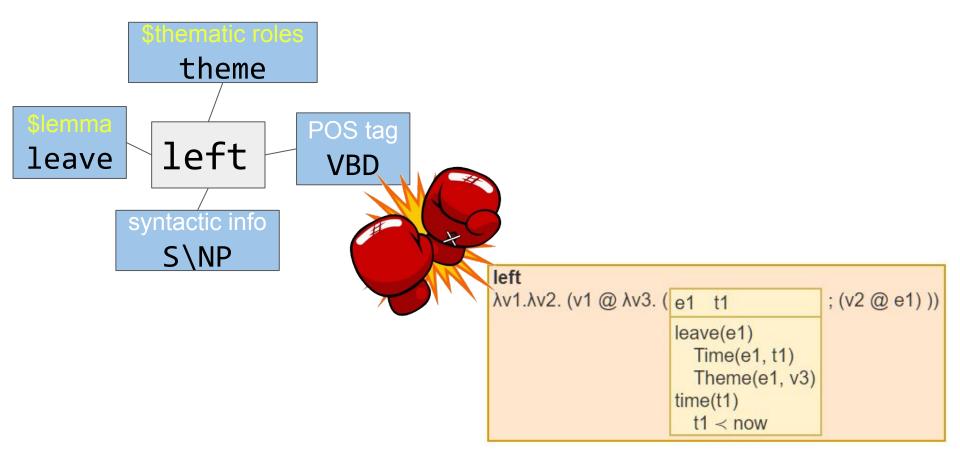
e1 t1 t2 male.n.02(x1) leave.v.01(e1) Time(e1, t1) Theme(e1, x1)time.n.08(t1) t1 X t2 t1 < nowmeasure.n.02(t2) t2 X now Unit(t2, day) Theme(t2, 3)



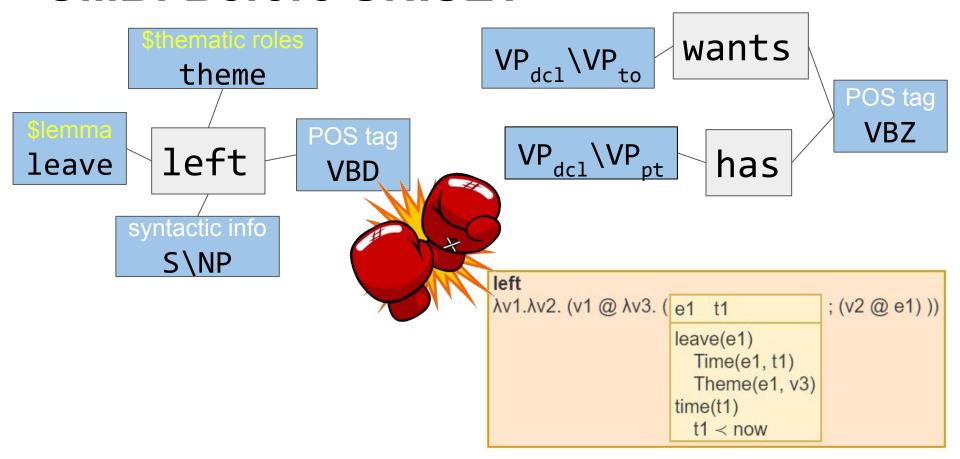
Goal

e1 t1 t2 male.n.02(x1) leave.v.01(e1) Time(e1, t1) Theme(e1, x1) time.n.08(t1) t1 X t2 t1 < nowmeasure.n.02(t2) t2 X now Unit(t2, day) Theme(t2, 3)

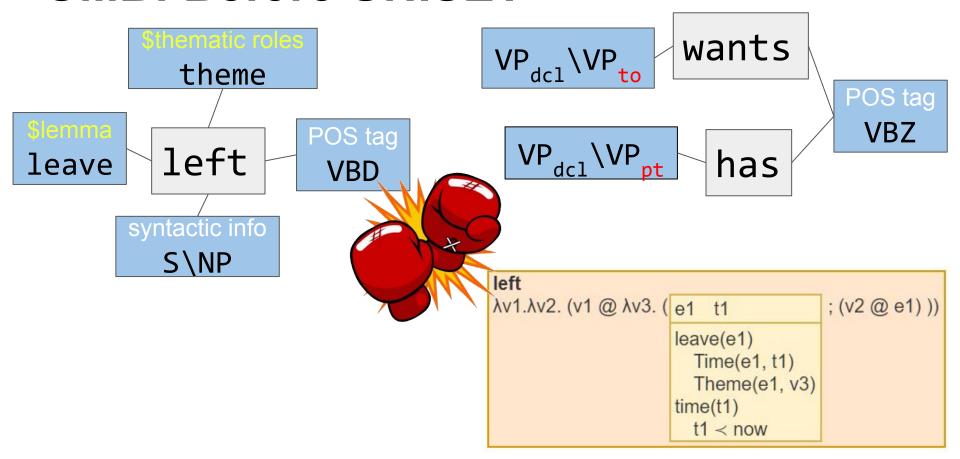
GMB: Before UNISET

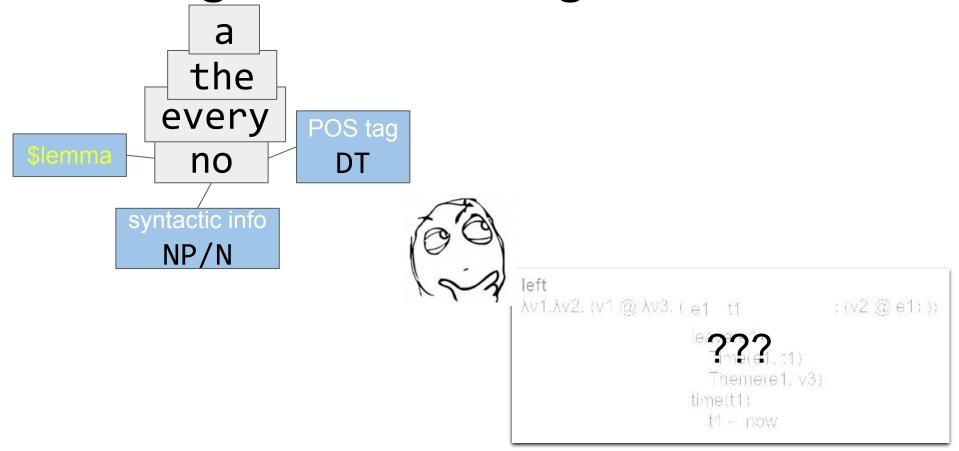


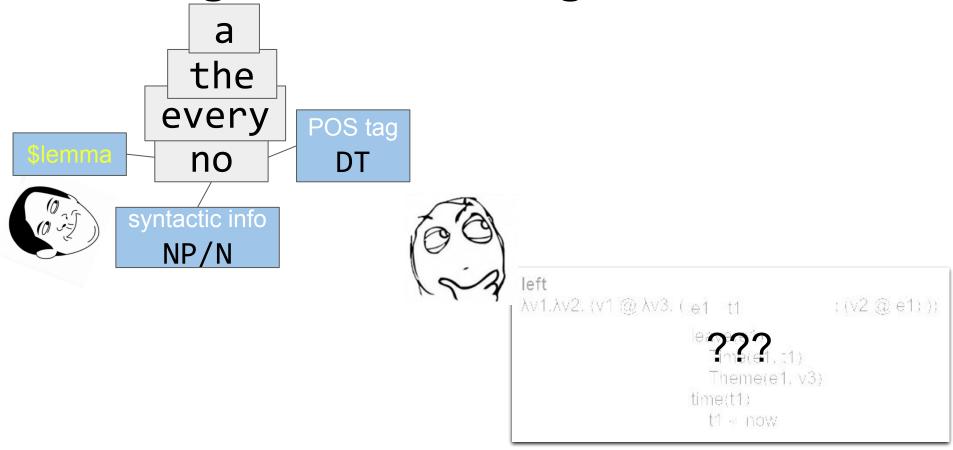
GMB: Before UNISET

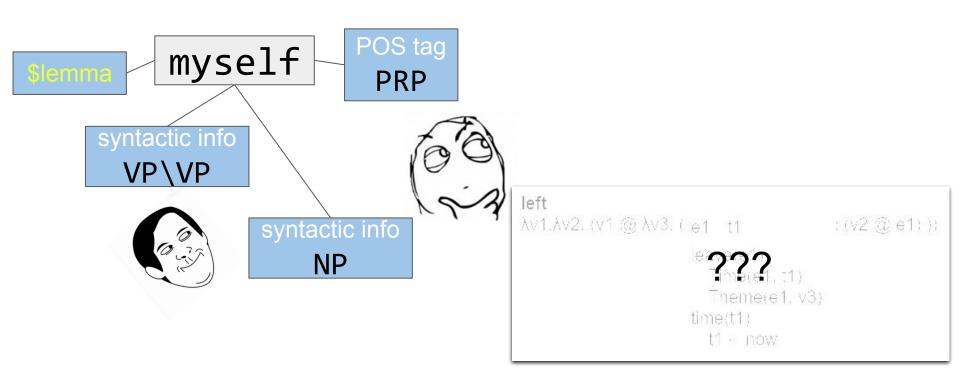


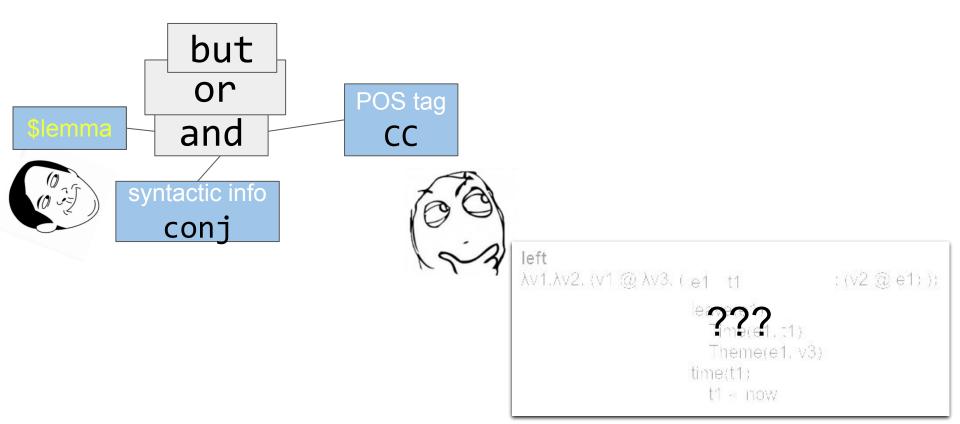
GMB: Before UNISET

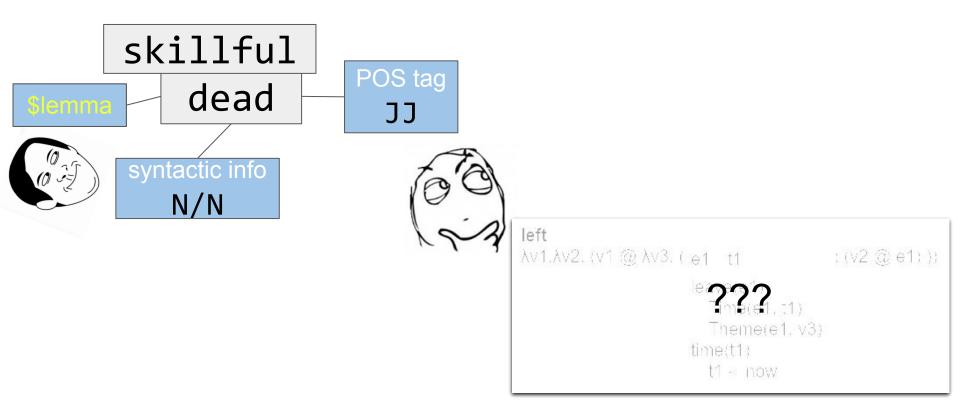










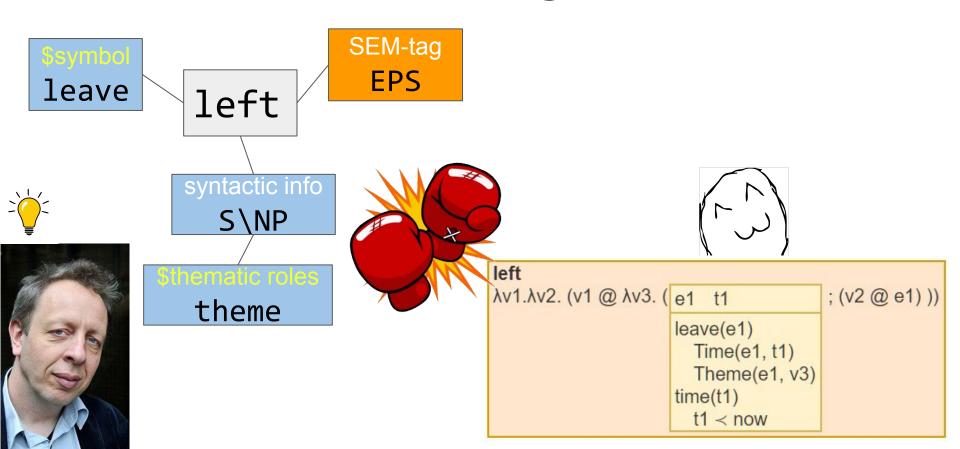


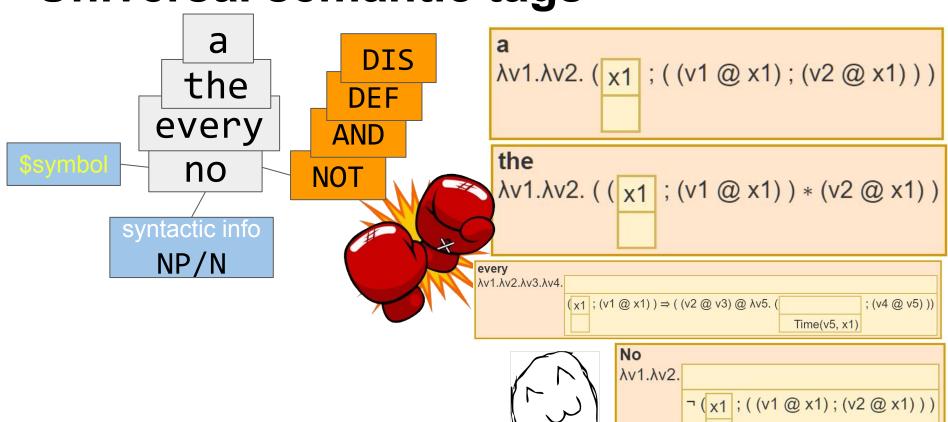
Something else is needed

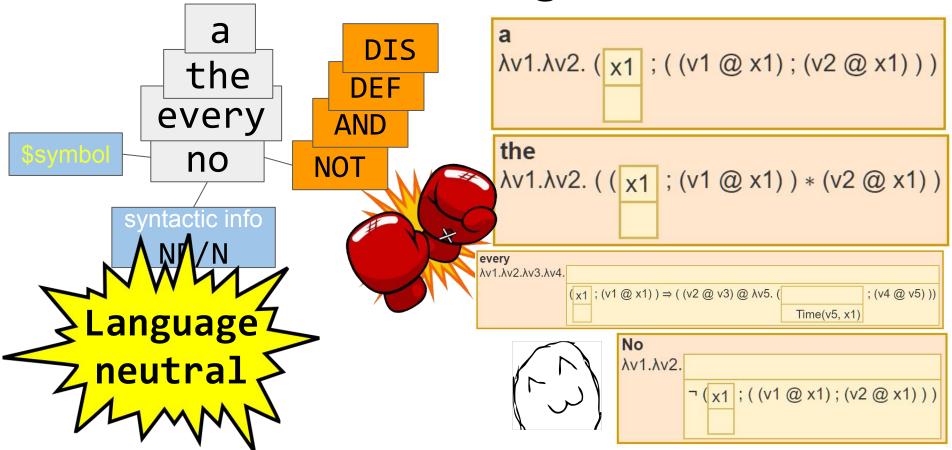
- POS tags lack fine-grained semantic information
- Relying on lemmas → not language neutral
- Relying on CCG categories →
 framework/language dependent
- Sometimes even a CCG category, lemma, and a POS-tag do not suffice: and, any











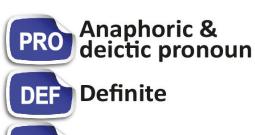
SEM tags for semantics

- Schema of lexical semantics is determined by a sem-tag and a syntactic category (SEM, CAT)
- Less sensitive to syntax (vs POS tags)
- Semantic info complements thematic roles, syntax and lemma.
- Generalizes over POS tags and Named Entity classes

UNIvesral SEemantic Tagset

- 73 sem-tags divided into 13 classes
- Under development (v0.7)
- Designed in a data-driven fashion (EN, NL, IT, DE)

two, six million, twice, 5 auantitv Vague quantity millions, many, enough red, crimson, light_blue Colour open, vegetarian, quickly **Intersective** Attribute skillful surgeon, tall kid Subsective **Privative** former, fake DEG 2 meters tall, 20 years old Degree **Intensifier** very, much, too, rather Relation in, on, of, after Score 3-0, grade A









EMP Emphasizing pro.

he, she, I, him

the, lo^{IT}, der^{DE}

my, her

blamed herself, each other

left himself











he, she, I, him

the, lo^{IT}, der^{DE}

my, her

blamed herself, each other

left himself

hi, bye alas, ah err who, which, ?



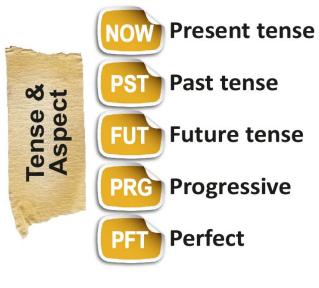
GRE Greeting & parting



Hesitation

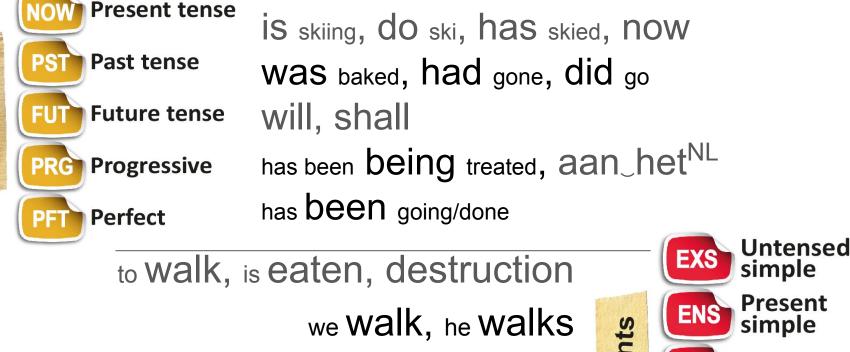


Interrogative



is skiing, do ski, has skied, now was baked, had gone, did go will, shall has been being treated, aan_het^{NL} has been going/done





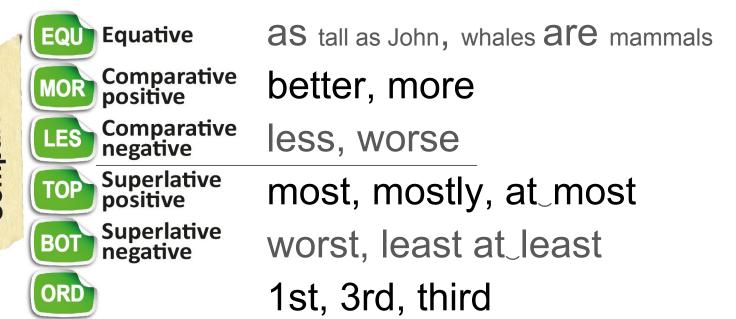
we Walk, he Walks
ate, went
is running
has eaten

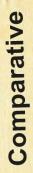
we Walk, he Walks

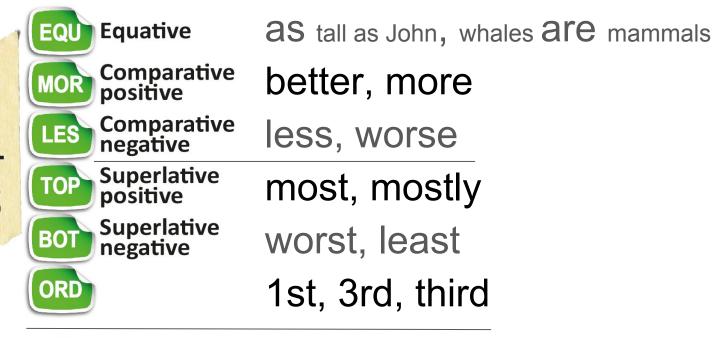
ate, went
is running
has eaten

we Walk, he Walks

ate, went
is running
has eaten









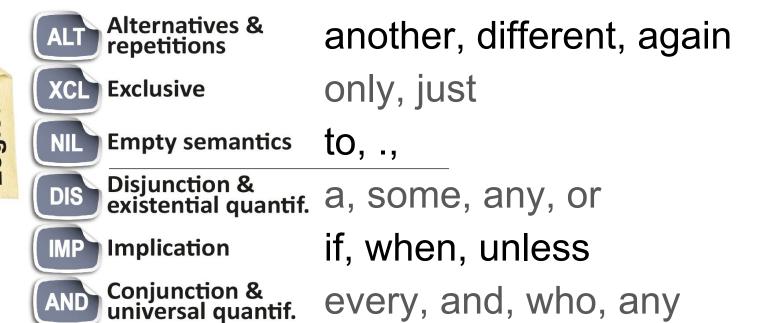
ROL Role

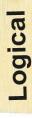
GRP Group

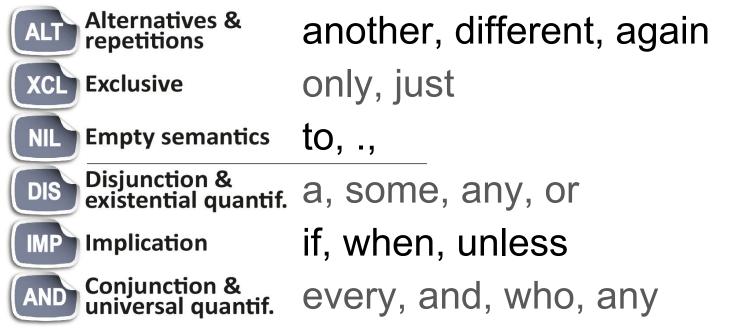
dog, person

student, brother, prof., victim

John and Mary gathered, a group of people







not, no, neither, without

must, should, have to might, could, perhaps, alleged, can



Necessity

Negation



DAT Full date	27.04.2017, 27/04/17
Dom Day of Month	27th December
Yoc Year of century	2017
Day of week	Thursday
Month of year	April
DEC Decade	80s, 1990s
CLO Clocktime	8:45 pm, 10 o'clock, noon

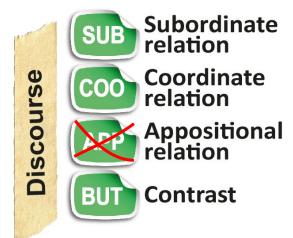


that, while, because

so, ;, and

which, —

but, yet



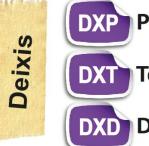
that, while, because

so, ;, and

which, —

but, yet

here, this, above just, later, tomorrow latter, former, above





Person

entity

origin

Unit of

URL

Literal use of names

Other names

Geo-political

Geo-political

Axl Rose, Sherlock Holmes				
Paris, Japan				
Parisian, French				
Alps, Nile				
IKEA, EU				
iOS_7				
Eurovision_2017				
meter, \$, %, degree Celsius				
112, info@mail.com				
http://pmb.let.rug.nl				
his name is John				
table 1a, equation (1)				

Ola a ula alla I I aluana a

Tagging & Semantics

Formal compositional semantics are less favoured:

- Semantics problems
- Difficult to scale up

Make formal semantics study modular

Tagging & Semantics

Formal compositional semantics are less favoured:

- Semantics problems
- Difficult to scale up

Make formal semantics study modular

NLP community loves tagging/labeling tasks

- Conceptually a simple task
- Create an annotated data
- Employ ML techniques for learning

Data & Results

- Gold EN documents (34.7K)
- Silver EN documents (1.6M)

Universal Semantic Tags

version	# en	# de	# it	# nl	silver inc.	release date	download
0.1.0	5438	0	0	0	yes	01-05-2018	19 MB ZIP file

- Baseline (UniGram) ~82%
- Stanford tagger ~88.8%
- NN tagger (AUX UPOS) ~92.7% (M. Abdou)

Challenges

- Account for wide-coverage compositional semantics
- Keep UNISET independent from CCG
- Prevent the number of sem-tags from increasing

Conclusion

- Facilitates determining lexical semantics
- Contributes to cross-lingual applications
- Useful for other NLP applications
- Useful for other semantic parsers or RTE systems: (ccg2lambda, LangPro, UDepLambda,...)

Future work

- Cover more semantic phenomena (data-driven)
- Measure an inter-annotator agreement
- Reorganize tagset to simplify learning

