States, events, and generics:

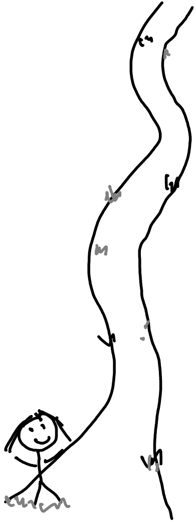
computational modeling of situation entity types

Annemarie Friedrich

October 23, 2018

Thanks to: Manfred Pinkal (Universität des Saarlandes)
Alexis Palmer (University of North Texas)
& all of my other collaborators

Annemarie Friedrich



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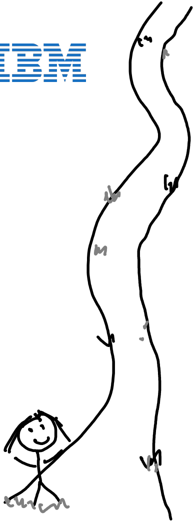

B.Sc. Applied Computer Science

- Text analysis

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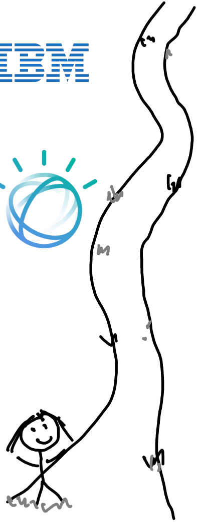

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- Question answering

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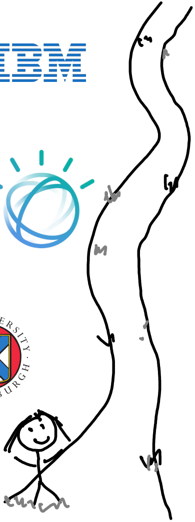

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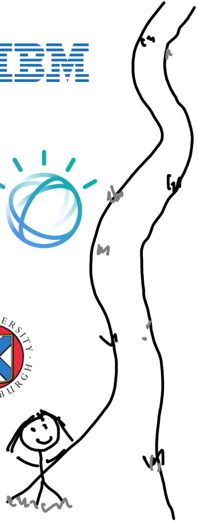

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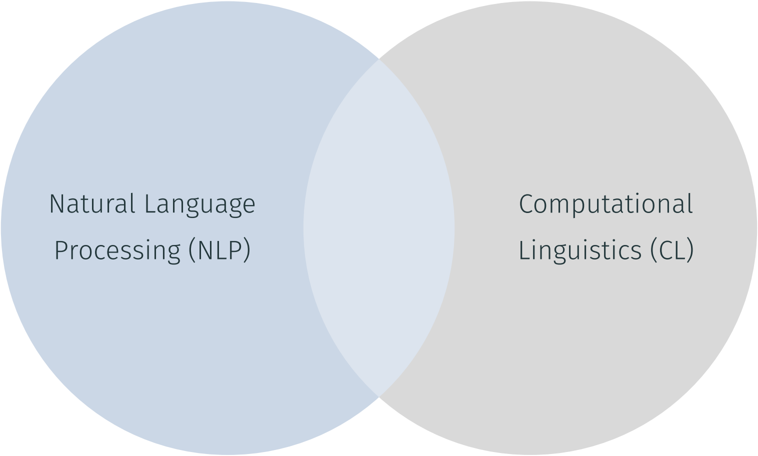
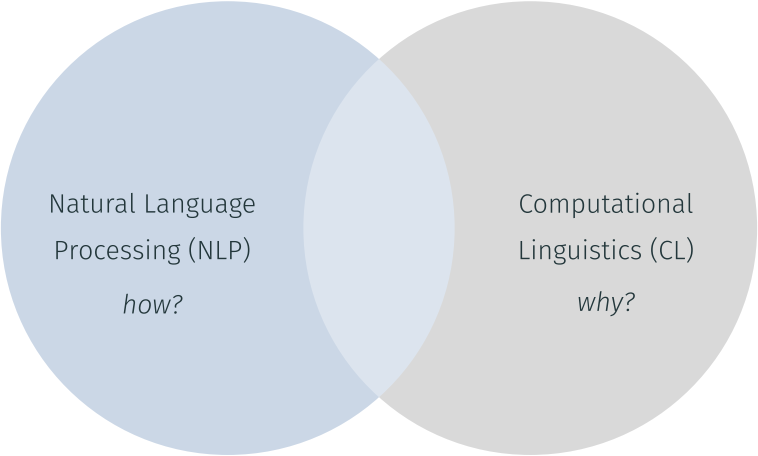
PostDoc

Don’t panic ☺


Natural Language
Processing (NLP)
Computational
Linguistics (CL)

Don’t panic ☺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how?
Computational Linguistics (CL)
why?

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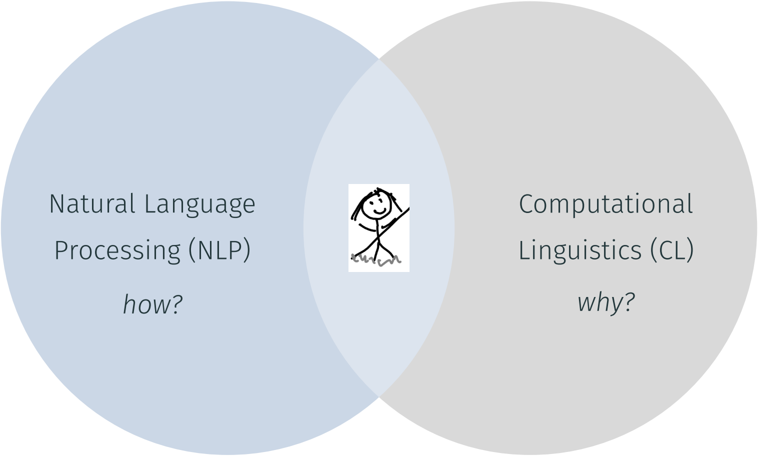
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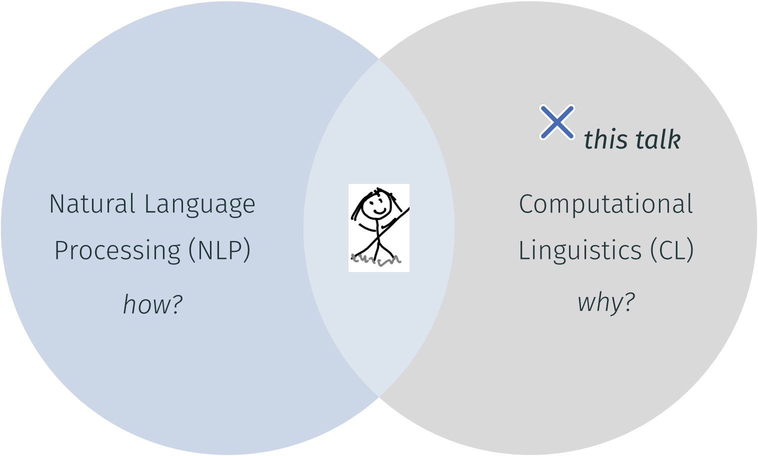
this talk
Natural Language
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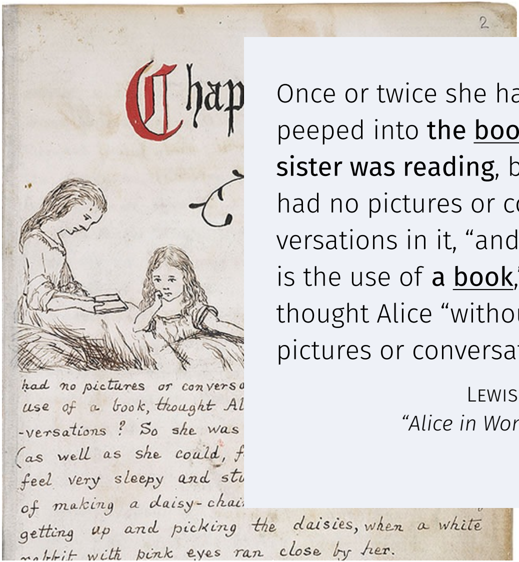
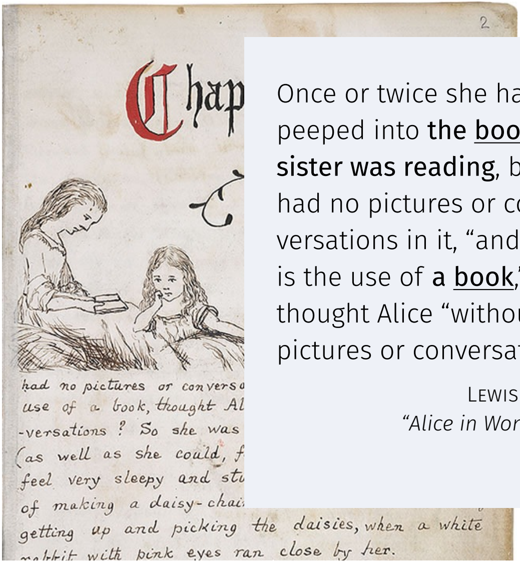
Motivation: coreference resolution



Once or twice she had peeped into **the <u>book</u> her sister was reading**, but it had no pictures or conversations in it, "and what is the use of **a <u>book</u>**," thought Alice "without pictures or conversations?"

LEWIS CARROLL:
"Alice in Wonderland"

Motivation: coreference resolution



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LEWIS CARROLL:
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particular book

kind

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LEWIS CARROLL: *"Alice in Wonderland"*

[Nedoluzhko, 2013]

particular book

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generics

Motivation: temporal relation extraction

The rabbit took out his watch.

Alice started to her feet.

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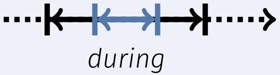

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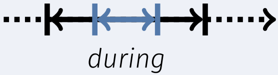


aspect

Aspect

aka aktionsart

[Vendler, 1957]
[Bach, 1986]

Aspect

aka aktionsart

[Vendler, 1957]
[Bach, 1986]

The ship moved. **event**

Aspect

aka aktionsart

[Vendler, 1957]
[Bach, 1986]

The ship moved.   **event**

Aspect

aka aktionsart

[Vendler, 1957]
[Bach, 1986]

The ship moved. **event**

The ship was moving. **ongoing event / process**

Aspect

aka aktionsart

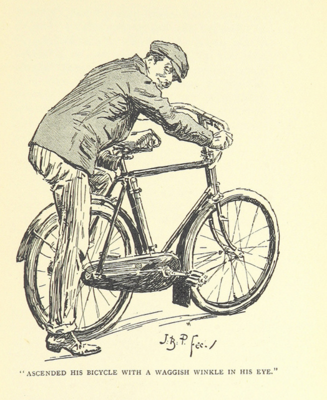
[Vendler, 1957]
[Bach, 1986]

The ship moved. **event** 

The ship was moving. **ongoing event / process** 

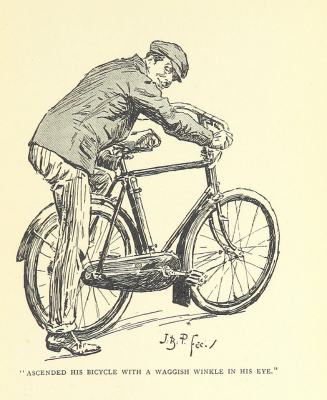
The ship was in motion. **state** 

Generics: habituals



Mike cycled to work. episodic event

Generics: habituals



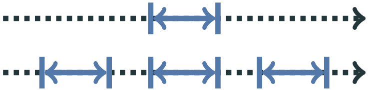
"ASCENDED HIS BICYCLE WITH A WAGGISH WINKLE IN HIS EYE."

generalization over situations

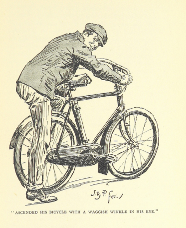
[Krifka et al., 1995]

Mike cycled to work. **episodic event**

Mike cycles to work. **habitual**



Generics: reference to kinds

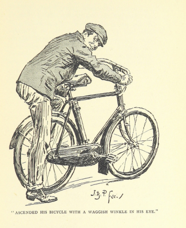


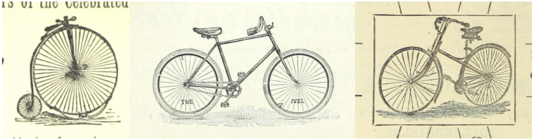
Mike's bike is blue.

particular bike

Generics: reference to kinds

[Krifka et al., 1995]





Mike's bike is blue.

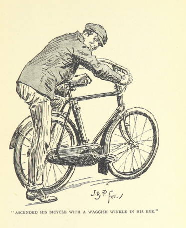
particular bike

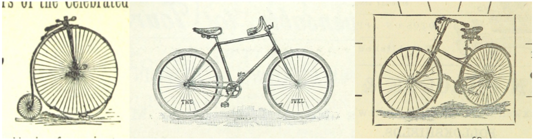
Bicycles have two wheels.

generalization over members of a kind

Generics: reference to kinds

[Krifka et al., 1995]





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Bicycles have two wheels.
generalization over members of a kind

The bicycle was invented in the 19th century.
reference to kind

Generics: reference to kinds

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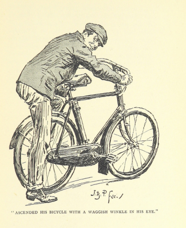

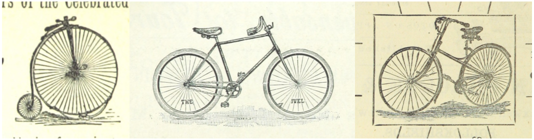

Mike's bike is blue.
particular bike

entailment

Bicycles have two wheels.
generalization over members of a kind

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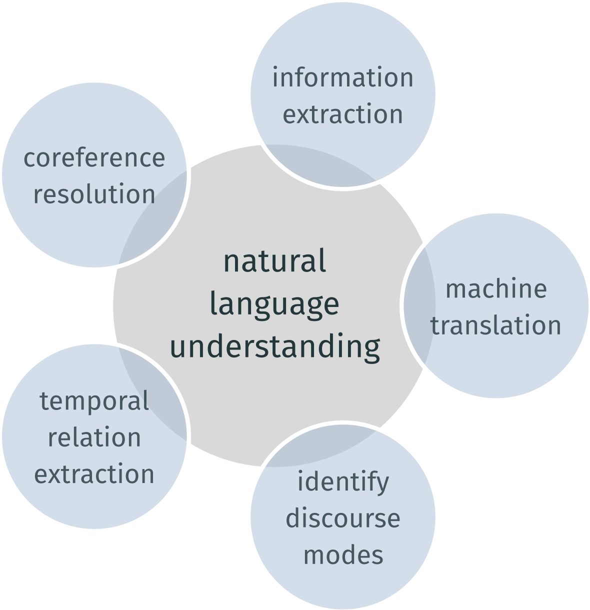
Why model these phenomena?



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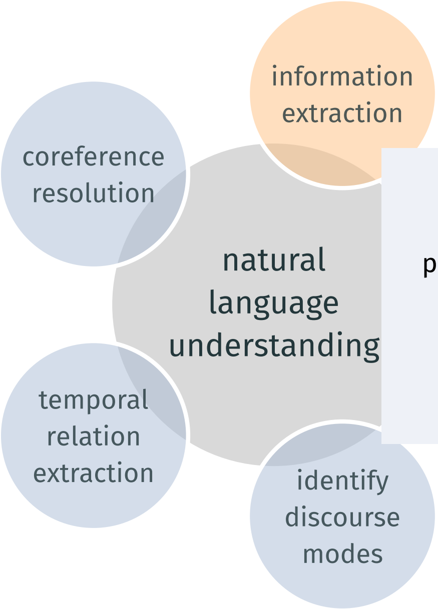


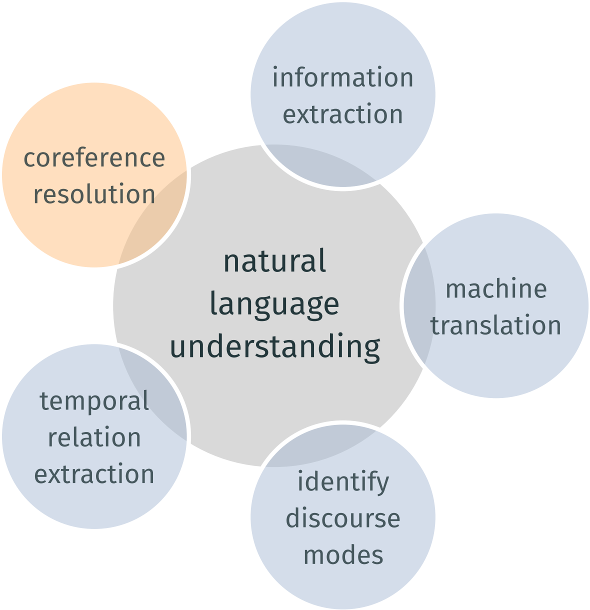
particular events, properties of individuals

vs.

generic knowledge

[Van Durme, 2009]

Why model these phenomena?



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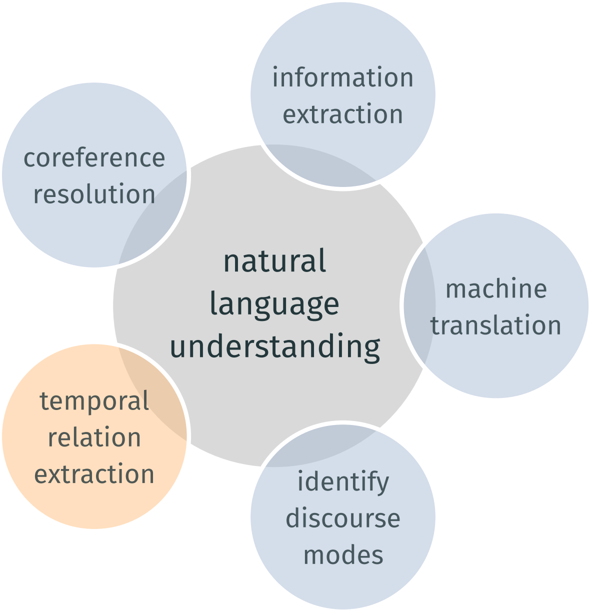

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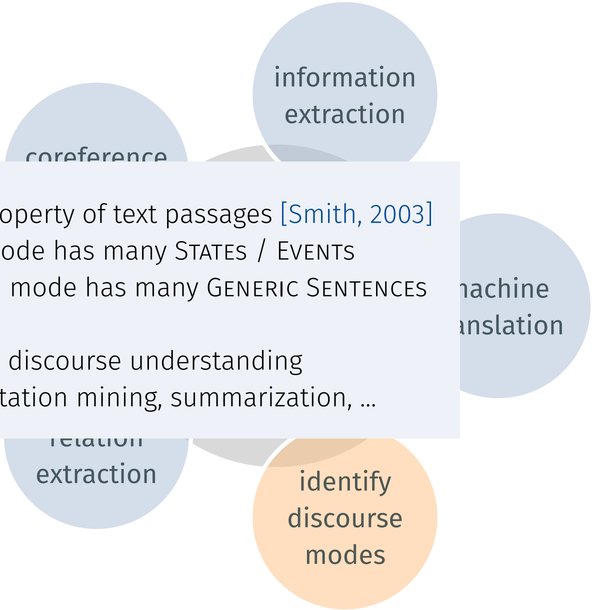


linguistic property of text passages [Smith, 2003]

Narrative mode has many STATES / EVENTS

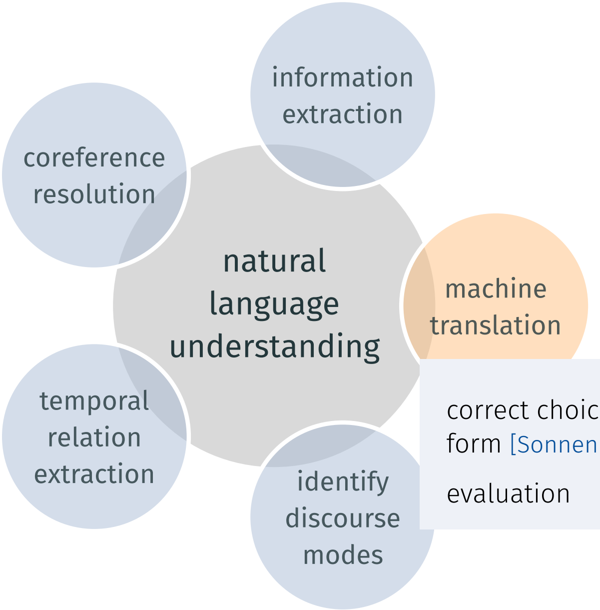
Information mode has many GENERIC SENTENCES

...

→ temporal discourse understanding

→ argumentation mining, summarization, ...

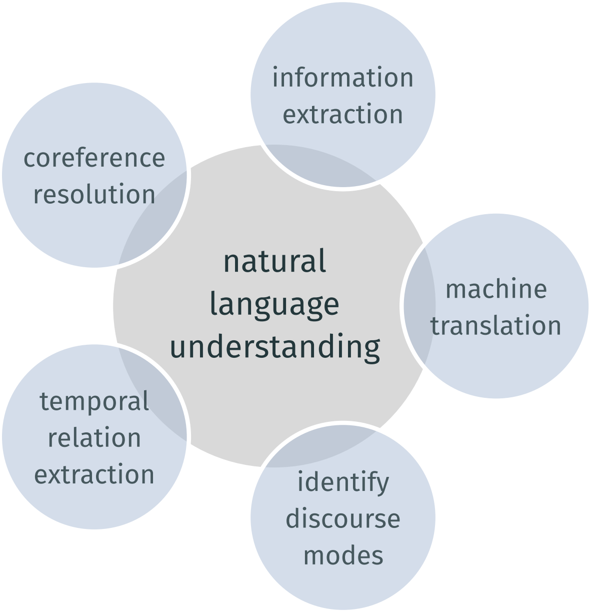
Why model these phenomena?



correct choice of aspectual form [Sonnenhauser, 2004]

evaluation

Why model these phenomena?



Overview of thesis work

generics	lexical aspect	habituals
reference to kinds	state vs. event	generalization over situations
[Friedrich & Pinkal, ACL 2015] [Friedrich et al., LAW 2015]	[Friedrich & Palmer, ACL 2014]	[Friedrich & Pinkal, EMNLP 2015]

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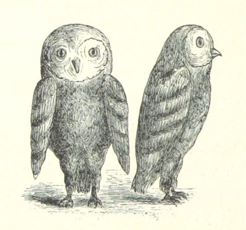
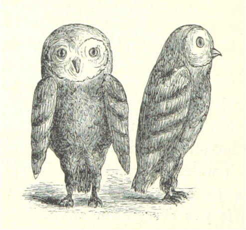


Situation entity types [Smith, 2003] [Palmer et al., 2007]

STATE	Julie likes Cooper.



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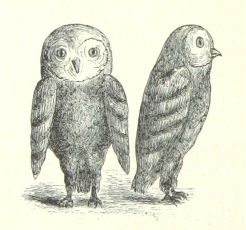
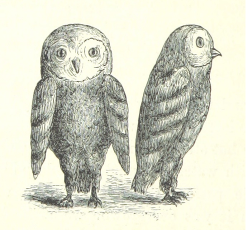


STATE	Julie likes Cooper.
EVENT	Julie met Cooper two years ago.

Situation entity types [Smith, 2003] [Palmer et al., 2007]



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REPORT	..., said the zookeeper.

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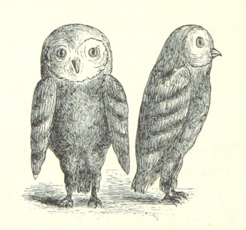

STATE	Julie likes Cooper.
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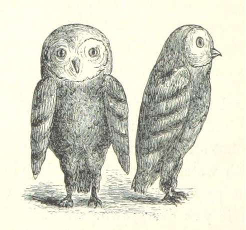
REPORT	..., said the zookeeper.
GENERIC SENTENCE	**Owls** are nocturnal animals.

Situation entity types [Smith, 2003] [Palmer et al., 2007]



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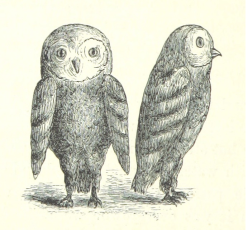

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IMPERATIVE	Catch the mouse!

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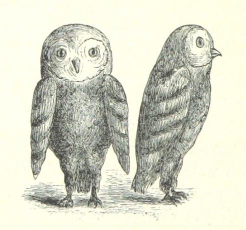

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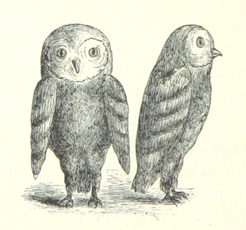
IMPERATIVE	Catch the mouse!
QUESTION	Why are there owls on your slides?

Situation entity types [Smith, 2003] [Palmer et al., 2007]



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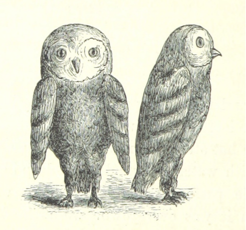

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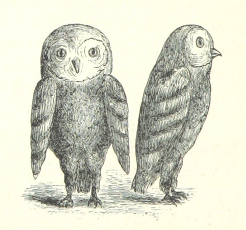
IMPERATIVE	Catch the mouse!
QUESTION	Why are there owls on your slides?

lexical aspect:
dynamic or ***stative***?

Situation entity types [Smith, 2003] [Palmer et al., 2007]



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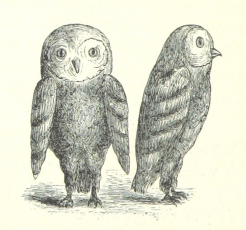
IMPERATIVE	
QUESTION	ur slides?

Does something happen repeatedly?
episodic or ***habitual***?

Situation entity types [Smith, 2003] [Palmer et al., 2007]



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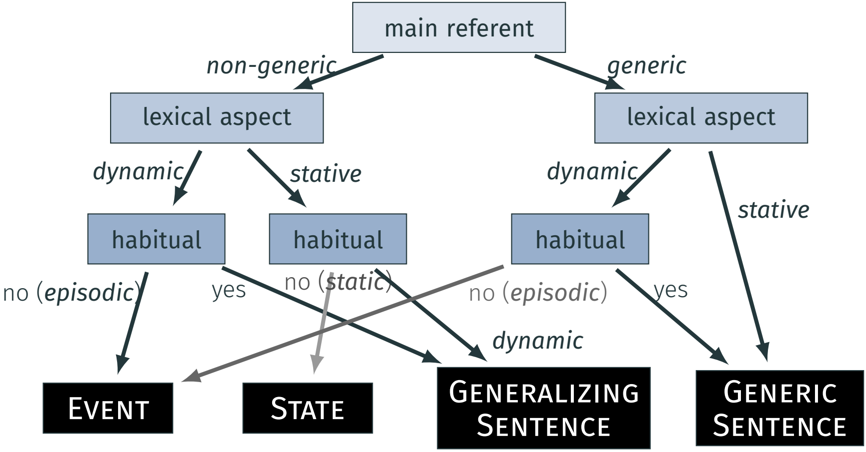
IMPERATIVE	Catch the mouse!
QUESTION	Why are there owls on your slides?

About kind/class or particular referent?
generic or ***non-generic***?

Annotation scheme

[Friedrich and Palmer, 2014b] [Friedrich et al., 2015]



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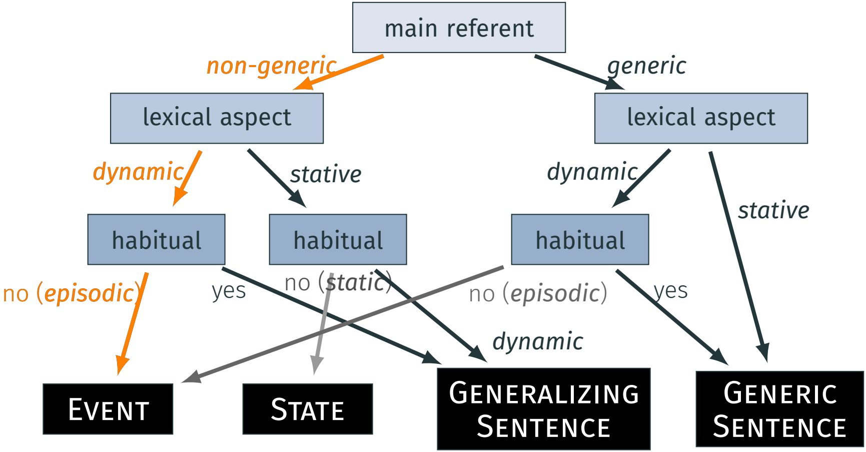

Mike cycled to work.

Annotation scheme

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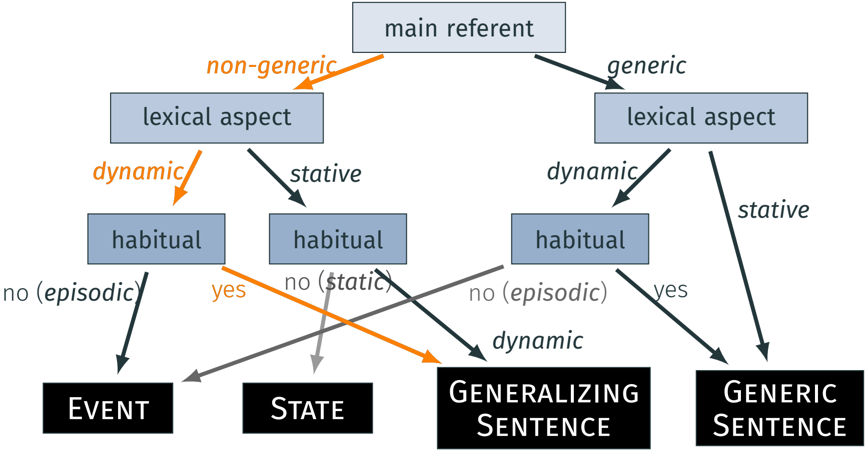

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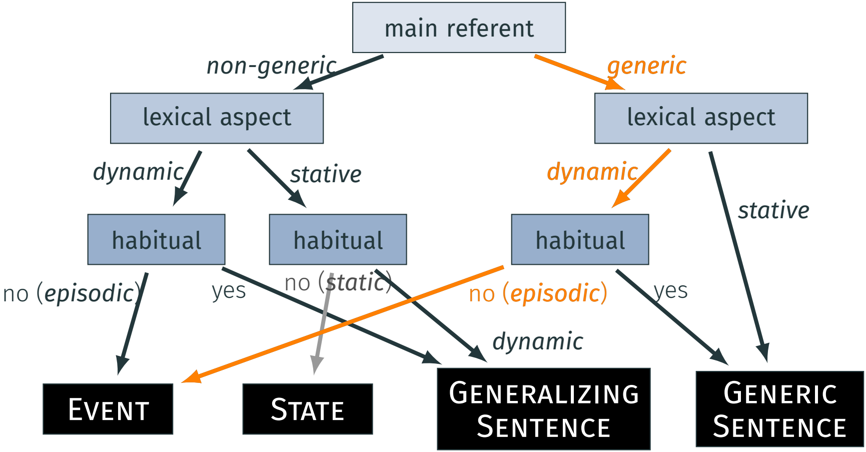
Annotation scheme

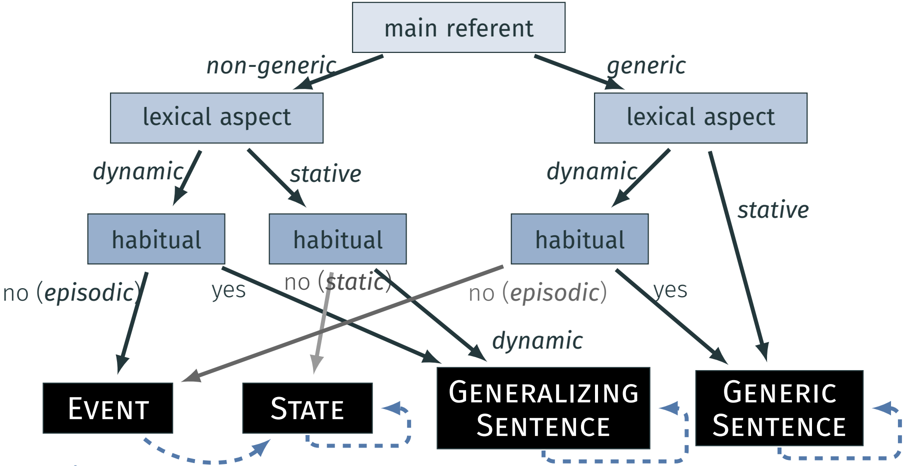
[Friedrich and Palmer, 2014b] [Friedrich et al., 2015]



The bicycle was invented in the 19th century.

Annotation scheme

[Friedrich and Palmer, 2014b] [Friedrich et al., 2015]



coercion: negation, modals, conditional, perfect, future

Data and annotation procedure

MASC
31,596 clauses
news, letters, fiction, journal, technical, travel, ...

Wikipedia
10,355 clauses
animals, science, sports, ethnic groups, ...

Data and annotation procedure

anc AMERICAN NATIONAL CORPUS

MASC
31,596 clauses
news, letters, fiction, journal, technical, travel, ...

Wikipedia
10,355 clauses
animals, science, sports, ethnic groups, ...

Clause segmentation
SPADE [Soricut and Marcu, 2003]
+ heuristics

Data and annotation procedure

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SPADE [Soricut and Marcu, 2003]
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manual annotation
training phase + written manual

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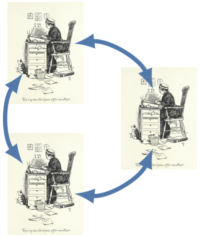
Clause segmentation
SPADE [Soricut and Marcu, 2003]
+ heuristics

manual annotation
training phase + written manual

gold standard
majority vote over labels of 3 annotators

Inter-annotator agreement

Fleiss' κ:
how much agreement
beyond chance?



Inter-annotator agreement

Fleiss' κ:
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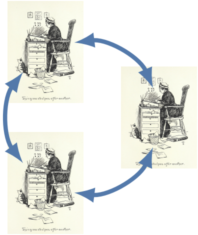
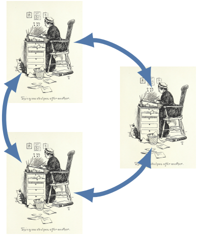


Annotation layer		MASC	Wiki
lexical aspect	***stative***	0.69	0.64
	dynamic		
	both		

Inter-annotator agreement

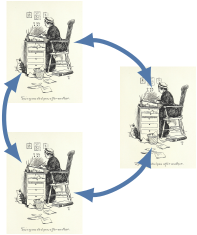
Fleiss' κ:
how much agreement beyond chance?



Annotation layer		MASC	Wiki
lexical aspect	*stative* *dynamic* *both*	0.69	0.64
main referent	*generic* *non-generic* *cannot decide*	0.69	0.65

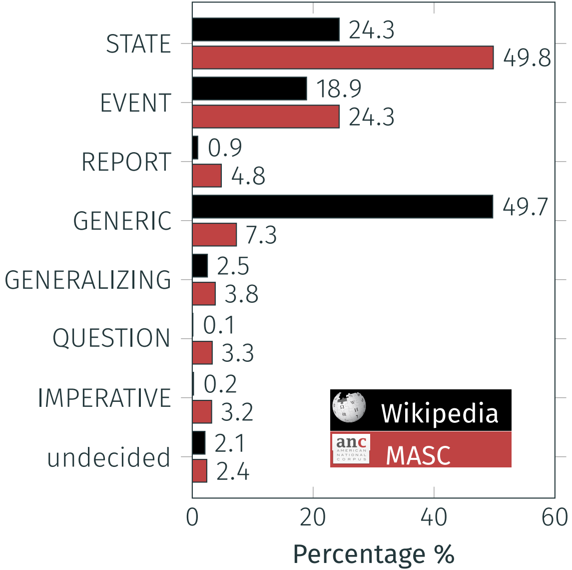
Inter-annotator agreement

Fleiss' κ:
how much agreement beyond chance?

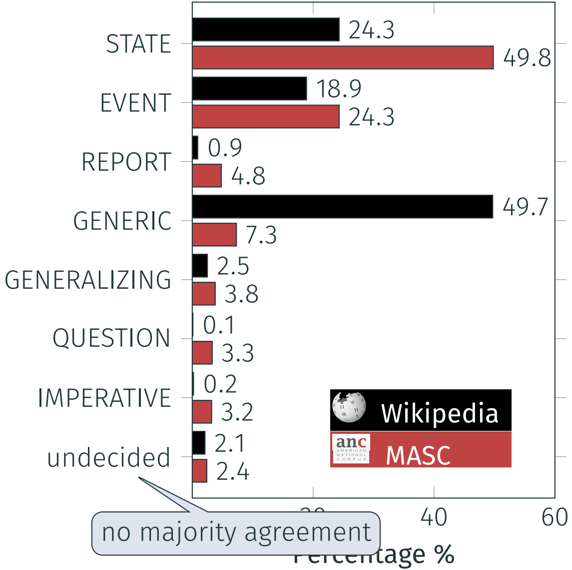


Annotation layer		MASC	Wiki
lexical aspect	*stative* *dynamic* *both*	0.69	0.64
main referent	*generic* *non-generic* *cannot decide*	0.69	0.65
habituality	*episodic* *habitual* *static* *cannot decide*	0.55	0.67

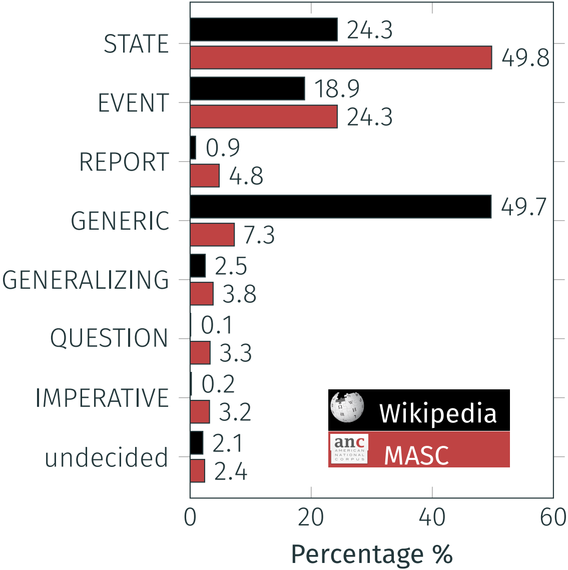
Situation entity types: distributions and agreement



Situation entity types: distributions and agreement

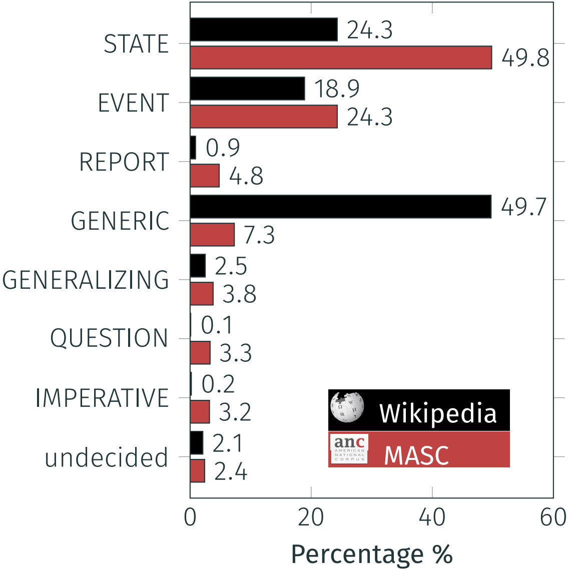


Situation entity types: distributions and agreement



Fleiss' κ [Krippendorff, 1980]	
STATE	0.67
EVENT	0.74
REPORT	0.80
GENERIC	0.68
GENERALIZING	0.43
QUESTION	0.91
IMPERATIVE	0.94

Situation entity types: distributions and agreement



Fleiss' κ [Krippendorff, 1980]

STATE	0.67
EVENT	0.74
REPORT	0.80
GENERIC	0.6
GENERALIZING	0.43
QUESTION	0.91
IMPERATIVE	0.94

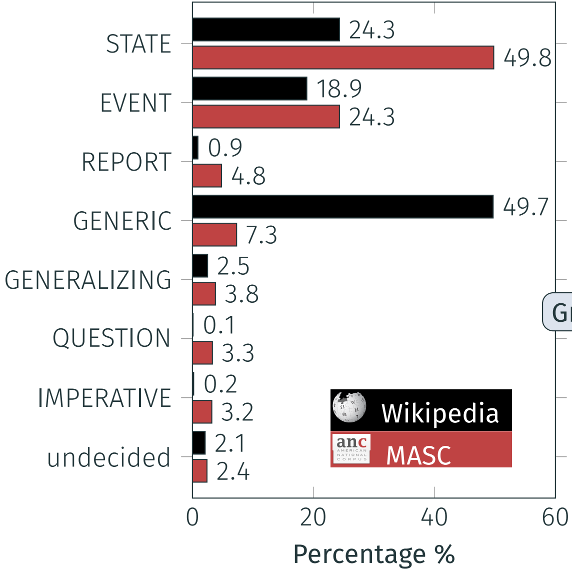
EVENT: easy

REPORT: easy

QUESTION: easy

IMPERATIVE: easy

Situation entity types: distributions and agreement



Fleiss' κ [Krippendorff, 1980]

STATE	0.67
EVENT	0.74
REPORT	0.80
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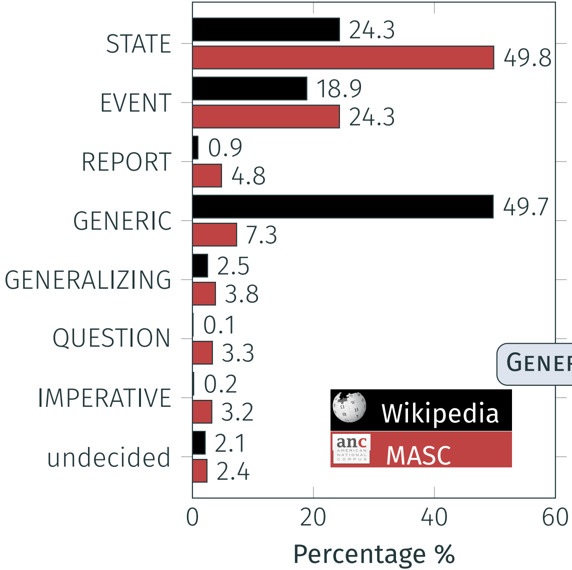
GENERALIZING	0.43
QUESTION	0.91
IMPERATIVE	0.94

GENERIC SENTENCES: difficult

Situation entity types: distributions and agreement



Fleiss' κ [Krippendorff, 1980]

STATE	0.67
EVENT	0.74
REPORT	0.80
GENERIC	0.68
GENERALIZING	0.43
[illegible]	[illegible]
IMPERATIVE	0.94

GENERALIZING SENTENCES: sparse

Overview of thesis work

computational modeling

corpus creation / analysis of agreement

linguistic background / annotation scheme

generics
reference to kinds
[Friedrich & Pinkal, ACL 2015]
[Friedrich et al., LAW 2015]

lexical aspect
state vs. event
[Friedrich & Palmer, ACL 2014]

habituals
generalization over situations
[Friedrich & Pinkal, EMNLP 2015]

situation entity types [Smith, 2003]
[Friedrich et al., ACL 2016], [Friedrich & Palmer, LAW 2014],
[Mavridou et al., LSDSem 2015], [Palmer & Friedrich, 2014]

Related work in computational linguistics

- modeling of aspectual classes
  - **Vendler classes** [Vendler, 1957]:
    Italian [Zarcone and Lenci, 2008], German [Hermes et al., 2015]
  - ***stative*** vs. ***dynamic*** [Siegel and McKeown, 2000]
  - **completedness** [Siegel and McKeown, 2000] [Loáiciga and Grisot, 2016]
- functions of tense [Reichart and Rappoport, 2010] [Zhang and Xue, 2014]
  - (episodic/future/...) event, habitual, state, general facts, ...
- modeling genericity
  - identifying genericity of NPs / reference to kinds [Reiter and Frank, 2010]
  - recognizing habituals [Mathew and Katz, 2009]
- labeling situation entities [Palmer et al., 2007]
  - data set: 20 texts / 4391 clauses from Brown corpus

Overview of thesis work

computational modeling

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[Friedrich et al., ACL 2016], [Friedrich & Palmer, LAW 2014],
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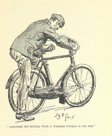
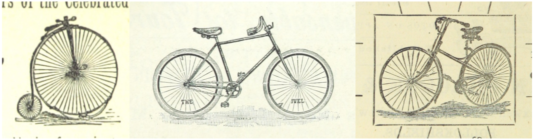
Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]





The bike is blue.

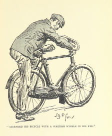
non-generic

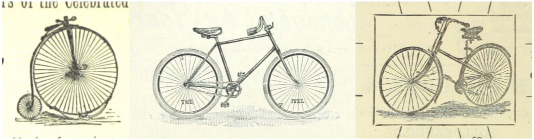
The bike was invented in the 19th century.

generic

Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]





The bike is blue.

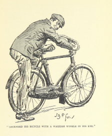
non-generic

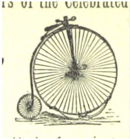
The bike was invented in the 19th century.

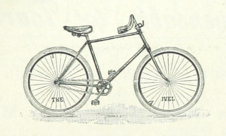
generic → form of NP **not sufficient for classification**

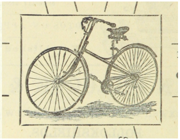
Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]









<u>The bike</u> is blue.

non-generic

<u>The bike</u> was invented in the 19th century.

generic

<u>form of NP</u> not sufficient for classification

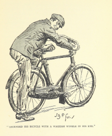
Mike keeps fixing his **<u>bicycle</u>**.

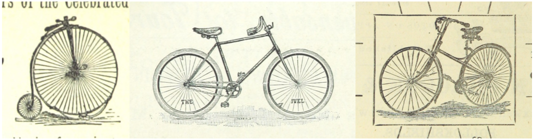
<u>The bicycle</u> has undergone continual adaptation and improvement.

non-generic

Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]





The bike is blue.

non-generic

The bike was invented in the 19th century.

generic → form of NP **not sufficient for classification**

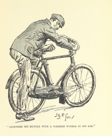
Bicycles were introduced in the 19th century in Europe.

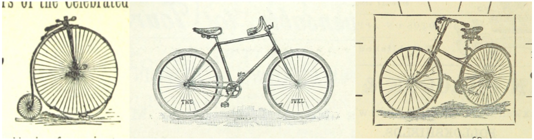
The bicycle has undergone continual adaptation and improvement.

generic

Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]





The bike is blue.

non-generic

The bike was invented in the 19th century.

generic

→ **form of NP not sufficient for classification**

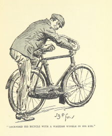
> Bicycles were introduced in the 19th century in Europe.
>
> The bicycle has undergone continual adaptation and improvement.

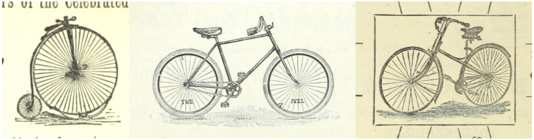
generic

→ discourse context matters

Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***? [Friedrich & Pinkal, ACL 2015]





The bike is blue. The bike was invented in the 19th century.

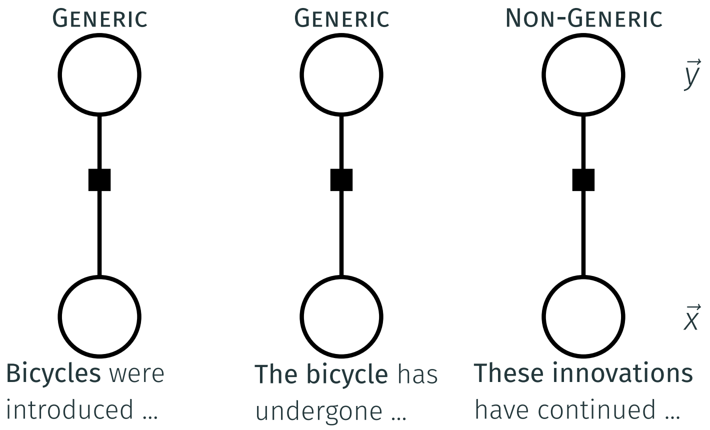
non-generic *generic* → **form of NP not sufficient for classification**

Bicycles were introduced in the 19th century in Europe.

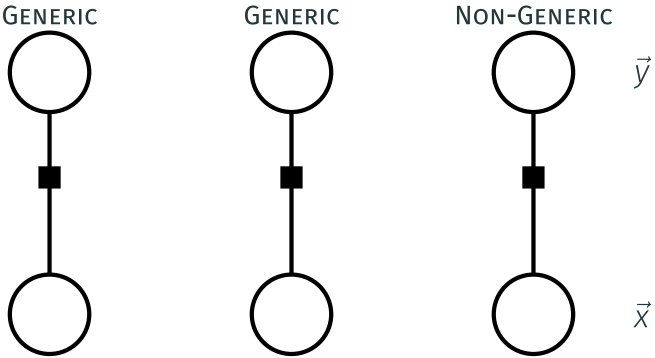
[Reiter and Frank, 2010] **The bicycle** has undergone continual adaptation and improvement. *generic*

→ discourse context matters

Discourse-sensitive identification of generic expressions



Discourse-sensitive identification of generic expressions



Bicycles were introduced …

barePlural = T
simplePast = T
…

The bicycle has undergone …

barePlural = F
perfect = T
…

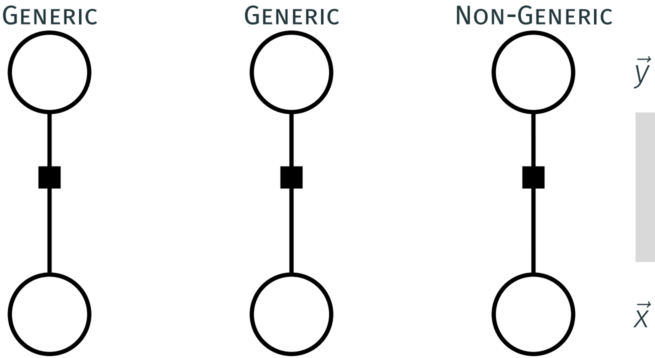
These innovations have continued …

barePlural = F
countable = Y
…

syntactic-semantic features

CRF

Discourse-sensitive identification of generic expressions



maximum entropy model (MaxEnt)

$P(y|x)$

Bicycles were introduced ...

barePlural = T
simplePast = T
...

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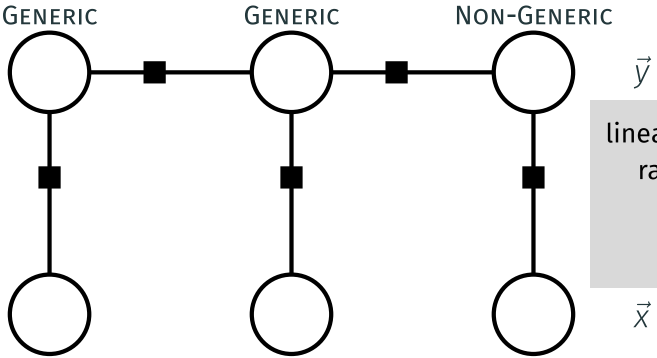

linear chain conditional random field (CRF)

$P(\vec{y}|\vec{x})$

`toolkit: CRF++`

Bicycles were introduced …

barePlural = T
simplePast = T
…

The bicycle has undergone …

barePlural = F
perfect = T
…

These innovations have continued …

barePlural = F
countable = Y
…

syntactic-semantic features

CRF

Syntactic-semantic features `https://github.com/annefried/sitent`

Implementation based on `dkpro` [Eckart de Castilho and Gurevych, 2014] and `Stanford CoreNLP` [Manning et al., 2014]

Syntactic-semantic features `https://github.com/annefried/sitent`

Implementation based on `dkpro` [Eckart de Castilho and Gurevych, 2014] and `Stanford CoreNLP` [Manning et al., 2014]

The bicycle has **undergone** continual adaptation and improvement.

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The bicycle has **undergone** continual adaptation and improvement.

main verb
tense
voice
progressive
perfect
lemma
WordNet hypernyms
linguistic indicators
...

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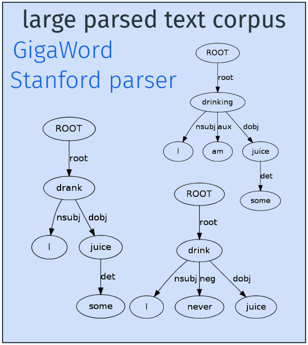
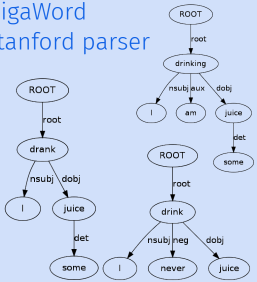


Linguistic indicators

[Siegel and McKeown, 2000]

Syntactic-semantic features https://github.com/annefried/sitent

large parsed text corpus
GigaWord
Stanford parser



Linguistic indicators

[Siegel and McKeown, 2000]

past/present tense	frequency	perfect
progressive	negation	particles
in-PP	for-PP	no subject
temp./manner/evaluation/contin. adverbs		

counts for each **verb type**

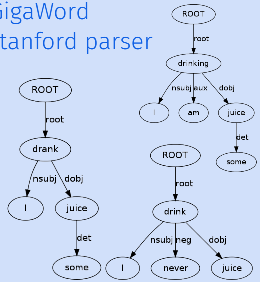
Syntactic-semantic features

https://github.com/annefried/sitent

large parsed text corpus

GigaWord

Stanford parser



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[Siegel and McKeown, 2000]

past/present tense	frequency	perfect
progressive	negation	particles
in-PP	for-PP	no subject
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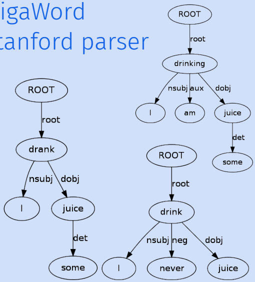
`counts` for each **verb type**

verb type: **drink** :: `ling_ind_past = 0.0927`

→ 9.27% of all instances of drink in corpus are in past tense

Syntactic-semantic features https://github.com/annefried/sitent

large parsed text corpus
GigaWord
Stanford parser



Linguistic indicators

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past/present tense	frequency	perfect
progressive	negation	particles
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`counts` for each **verb type**

verb type: **drink** :: `ling_ind_past = 0.0927`
→ 9.27% of all instances of drink in corpus are in past tense

→ 15 numeric features for each **verb type**
→ have been shown to **generalize across verb types** for aspectual classification tasks [Friedrich & Palmer, ACL 2014]

Syntactic-semantic features https://github.com/annefried/sitent

Implementation based on `dkpro` [Eckart de Castilho and Gurevych, 2014] and `Stanford CoreNLP` [Manning et al., 2014]

The bicycle has **undergone** continual adaptation and improvement.

main verb
tense
voice
progressive
perfect
lemma
WordNet hypernyms
linguistic indicators
...

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Implementation based on `dkpro` [Eckart de Castilho and Gurevych, 2014] and `Stanford CoreNLP` [Manning et al., 2014]

The bicycle has **undergone** continual adaptation and improvement.

main verb	**main referent** *(subject)*
tense	lemma
voice	determiner type
progressive	noun type
perfect	number
lemma	person
WordNet hypernyms	countability
linguistic indicators	WordNet senses
...	...

Syntactic-semantic features

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Implementation based on `dkpro` [Eckart de Castilho and Gurevych, 2014] and `Stanford CoreNLP` [Manning et al., 2014]

The bicycle has **undergone** continual adaptation and improvement.

main verb	**main referent** *(subject)*	**clause**
tense	lemma	adverbs
voice	determiner type	conditional
progressive	noun type	modal
perfect	number	negated
lemma	person	...
WordNet hypernyms	countability	
linguistic indicators	WordNet senses	
...	...	

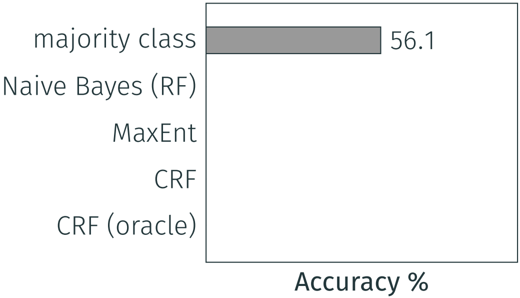
Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***?

Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***?

Wikipedia
10,355 clauses
document-wise cross validation



Discourse-sensitive identification of generic expressions

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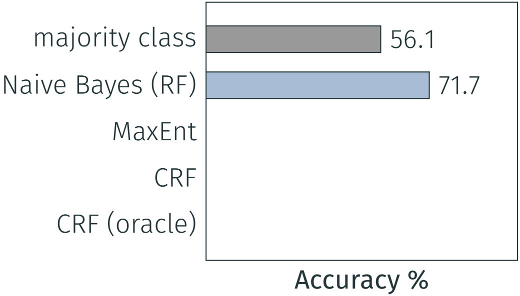

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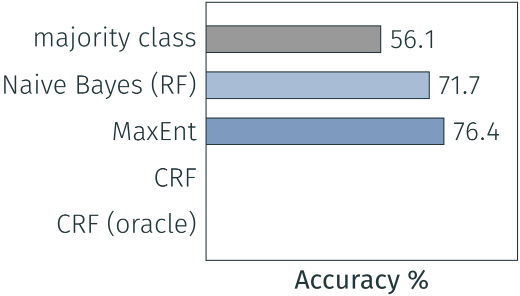

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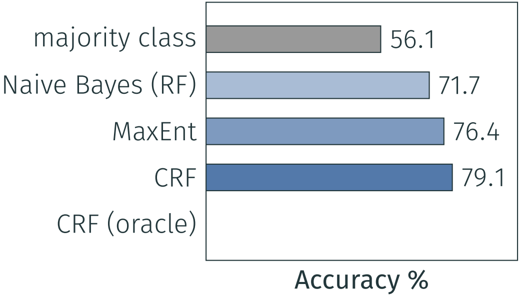

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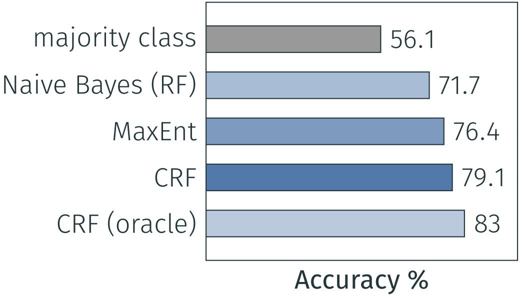


Discourse-sensitive identification of generic expressions

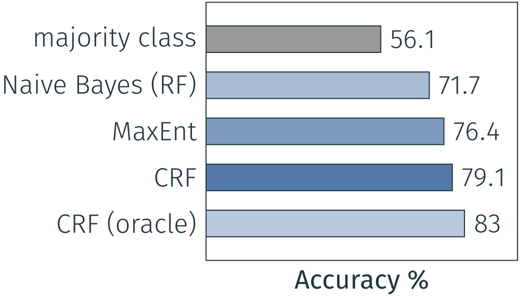
subject *non-generic* or *generic*?

Further findings

Wikipedia

10,355 clauses

document-wise cross validation



Discourse-sensitive identification of generic expressions

subject ***non-generic*** or ***generic***?

Wikipedia

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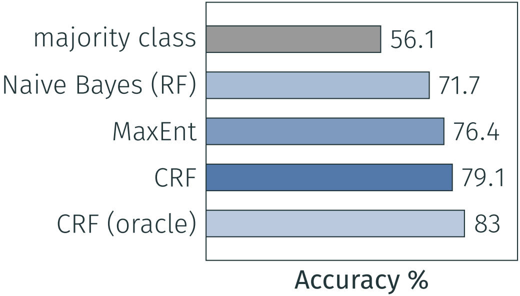

Further findings

- best results on **ACE-2** and **ACE-2005** data sets

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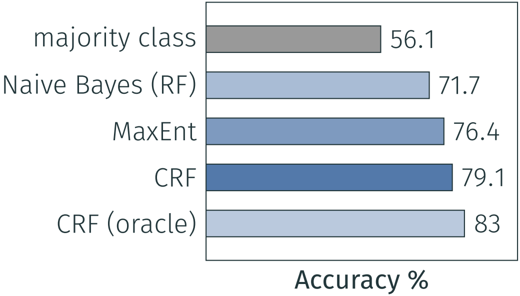

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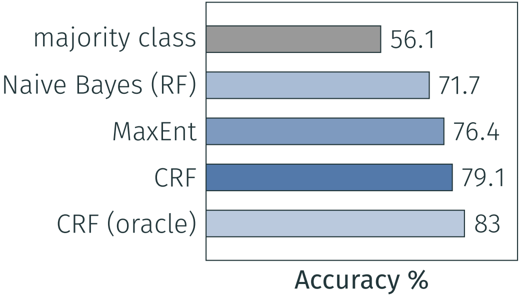

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- identification of **EVENTS related to kinds**

<u>Bikes</u> have two wheels. (GENERIC)
<u>The bike</u> was invented in the 19th century. (EVENT)

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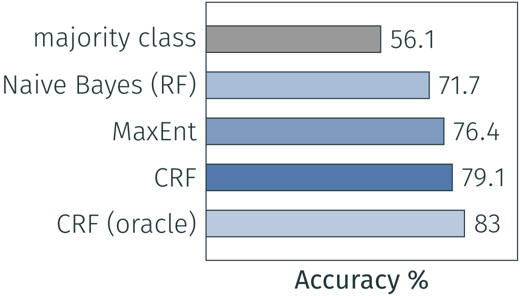

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  The bike was invented in the 19th century. (EVENT)

- sequence model often yields improvements when **coreference information** would be useful

Overview of thesis work

computational modeling

corpus creation / analysis of agreement

linguistic background / annotation scheme

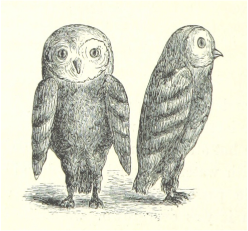
generics	lexical aspect	habituals
reference to kinds	state vs. event	generalization over situations
[Friedrich & Pinkal, ACL 2015] [Friedrich et al., LAW 2015]	[Friedrich & Palmer, ACL 2014]	[Friedrich & Pinkal, EMNLP 2015]

situation entity types [Smith, 2003]

[Friedrich et al., ACL 2016], [Friedrich & Palmer, LAW 2014], [Mavridou et al., LSDSem 2015], [Palmer & Friedrich, 2014]

Automatic classification of situation entity types

[Smith, 2003] [Palmer et al., 2007]



STATE	Julie likes Cooper.
EVENT	Julie met Cooper two years ago.
REPORT	..., said the zookeeper.
GENERIC SENTENCE	**Owls** are nocturnal animals.
GENERALIZING SENTENCE	Julie often teases Cooper.
IMPERATIVE	Catch the mouse!
QUESTION	Why are there owls on your slides?

Automatic classification of situation entity types

Step 1: Replication of and comparison to previous work

4391 clauses from Brown corpus [Francis and Kučera, 1979]
majority class STATE (35.3%), κ = 0.52 [Palmer et al., 2007]

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Accuracy (%)			
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MaxEnt	LB	MaxEnt	CRF
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lookback features: predicted labels for previous clauses

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first true **sequence labeling** approach
for situation entity types

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Reason:
GENERIC SENTENCES
cluster together

Automatic classification of situation entity types

Step 2: Full system

Features for clauses:

Automatic classification of situation entity types

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Automatic classification of situation entity types

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Automatic classification of situation entity types

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most important

Automatic classification of situation entity types

Step 2: Full system

7-way classification task
10-fold document-wise CV
dev set (80% of data)

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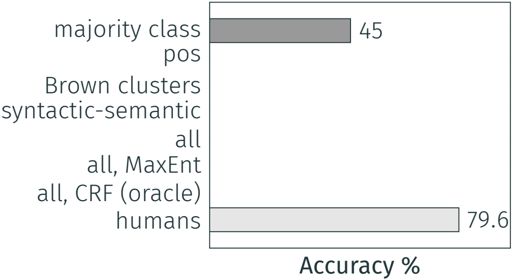

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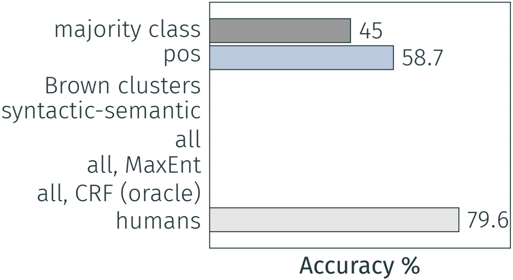

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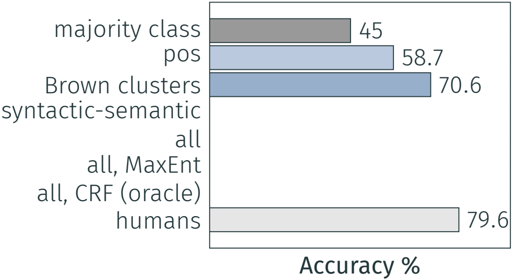

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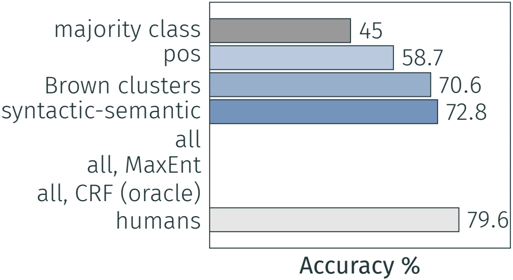

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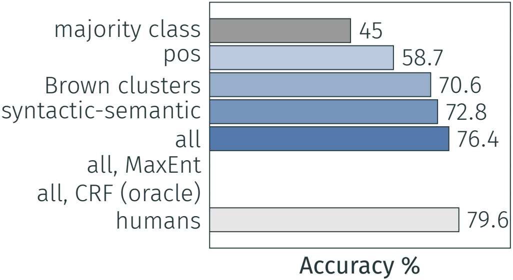

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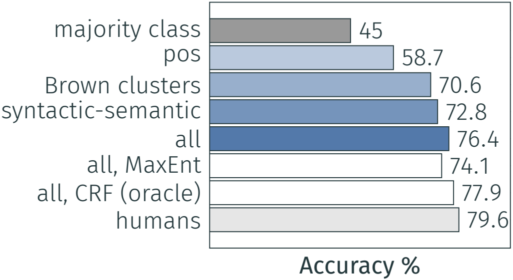

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7-way classification task
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findings validated on **heldout test set**

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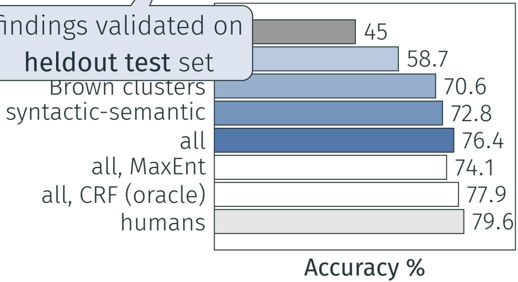

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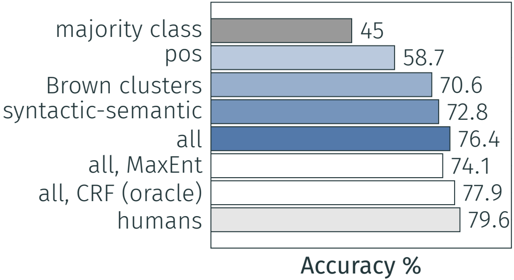

Further findings:

#1: model **trained directly on situation entity types** works better than pipelined model trained separately on the **subtasks**

Automatic classification of situation entity types

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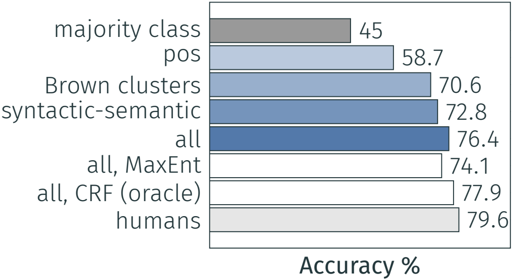

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#1: model **trained directly on situation entity types** works better than pipelined model trained separately on the **subtasks**

#2: good performance across **genres**
out-of-genre training data helps for infrequent types

Overview of thesis work

computational modeling

corpus creation / analysis of agreement

linguistic background / annotation scheme

generics
reference to kinds

[Friedrich & Pinkal, ACL 2015]
[Friedrich et al., LAW 2015]

lexical aspect
state vs. event

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Conclusion / contributions

computational modeling

corpus creation / analysis of agreement

n scheme

first large reliably annotated **corpus**
for situation entity types
(40,000 clauses, 13 genres)
and related aspectual + semantic phenomena

[Friedrich & Pinkal, ACL 2015]
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Conclusion / contributions

computational modeling

computational models for aspectual distinctions outperform prior approaches in each case; implementation publicly available

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Deep learning of situation entity types

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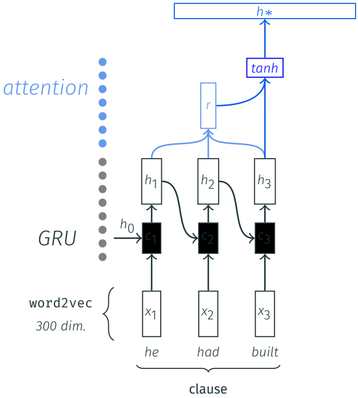
[Becker et al., 2017]



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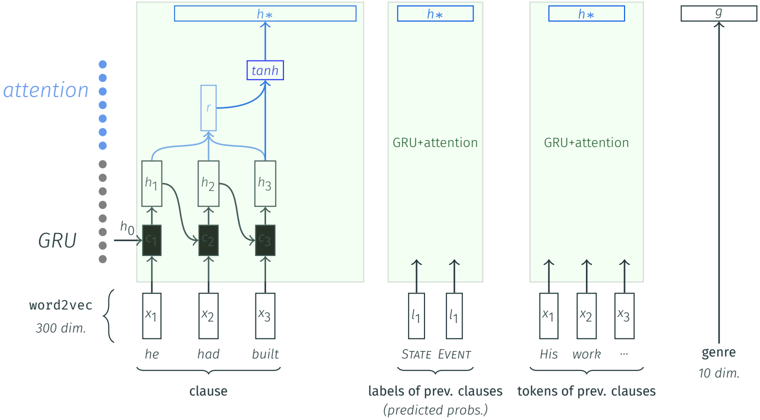

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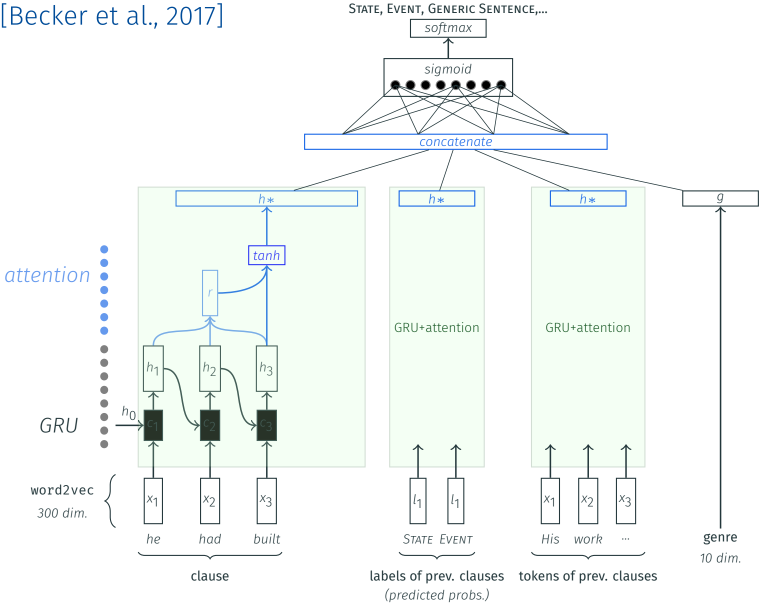

Deep learning of situation entity types

Situation entity type classification results on test set of MASC+Wiki.
[Dai and Huang, 2018]

Model	Macro-F1	Accuracy
CRF [Friedrich et al., 2016]	**69.3**	**74.7**
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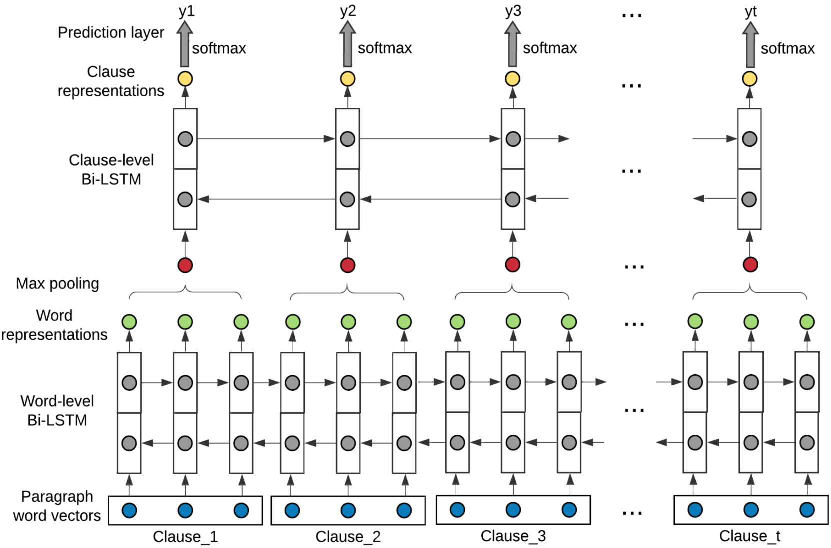
... but language-independent

Deep learning of situation entity types

Context-aware clause representations

[Dai and Huang, 2018]



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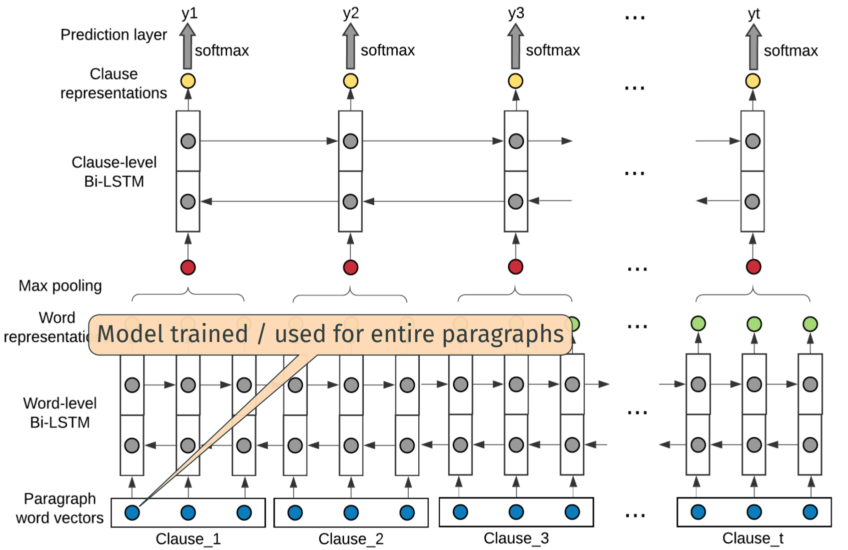

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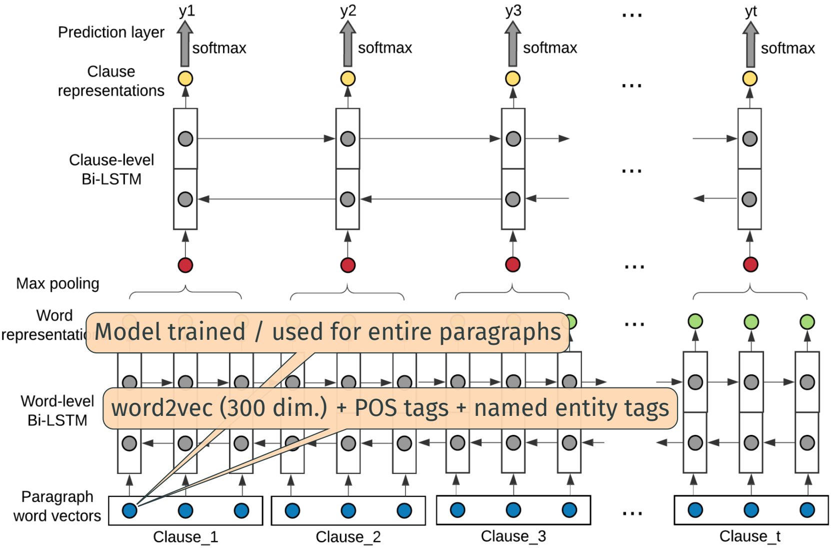

Model trained / used for entire paragraphs

word2vec (300 dim.) + POS tags + named entity tags

Deep learning of situation entity types

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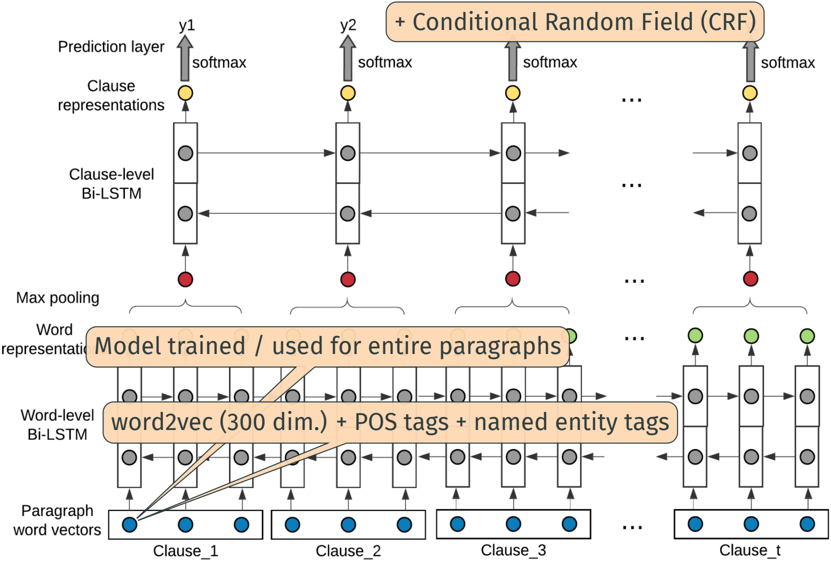

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humans	*80.0*	*78.1*

Conclusion / contributions / directions for future work

- Situation entity types can be annotated with **reasonable agreement** if broken down into related sub-tasks [Friedrich & Palmer, LAW 2014]

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    (e.g., different types of states: *John is tall* vs. *John is hungry* vs. *John can swim*)

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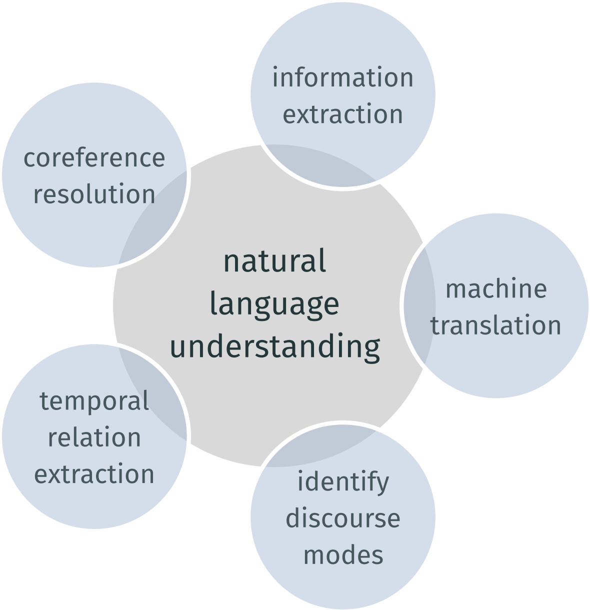
  - features describing **main verb** of clause are most important
  - using **discourse context** (CRF, paragraph embeddings, ...) is very informative

Directions for future work



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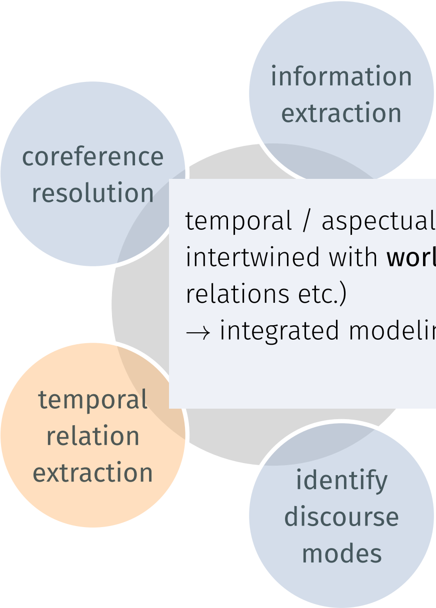
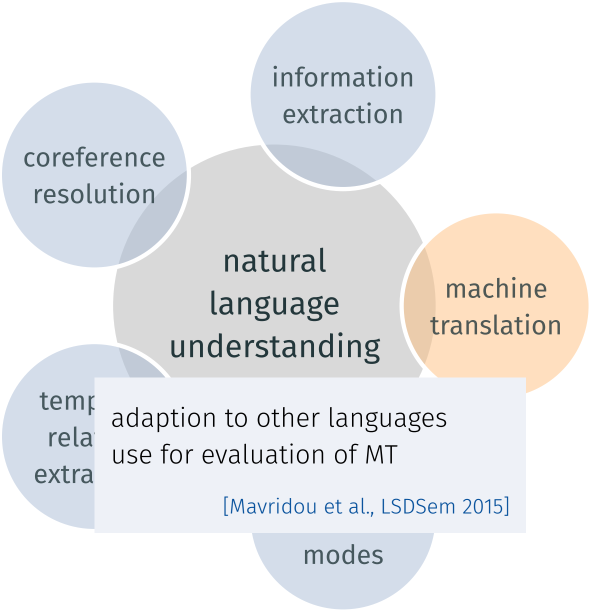


temporal / aspectual interpretation always intertwined with **world knowledge** (causal relations etc.)
→ integrated modeling?

[Steedman, 2012]

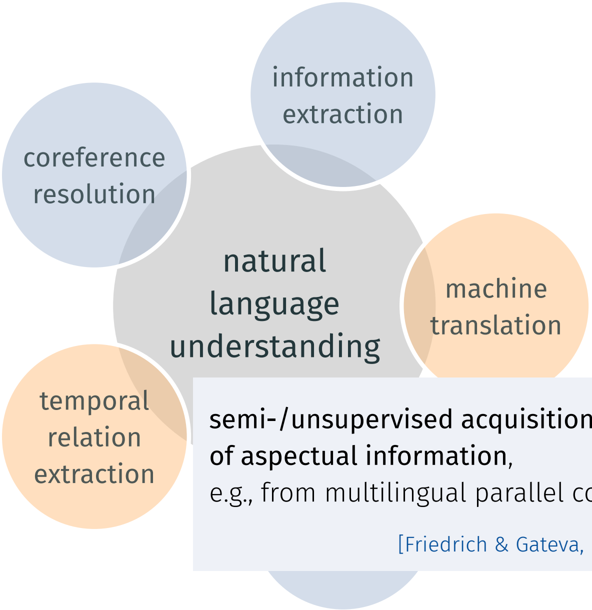
Directions for future work



adaption to other languages
use for evaluation of MT

[Mavridou et al., LSDSem 2015]

Directions for future work



semi-/unsupervised acquisition of aspectual information, e.g., from multilingual parallel corpora

[Friedrich & Gateva, EMNLP 2017]

States, events, and generics: computational modeling of situation entity types

computational modeling

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linguistic background / annotation scheme

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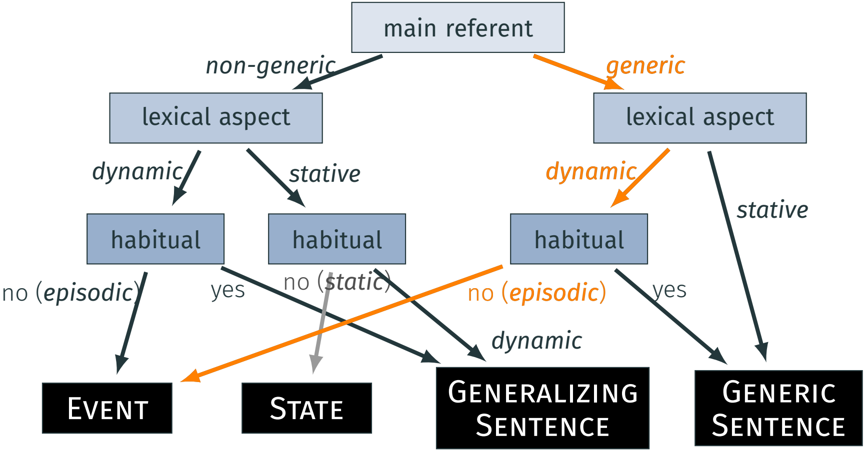
Backup Slides

Annotation scheme

[Friedrich and Palmer, 2014b] [Friedrich et al., 2015]



The bicycle was invented in the 19th century.

Annotation scheme

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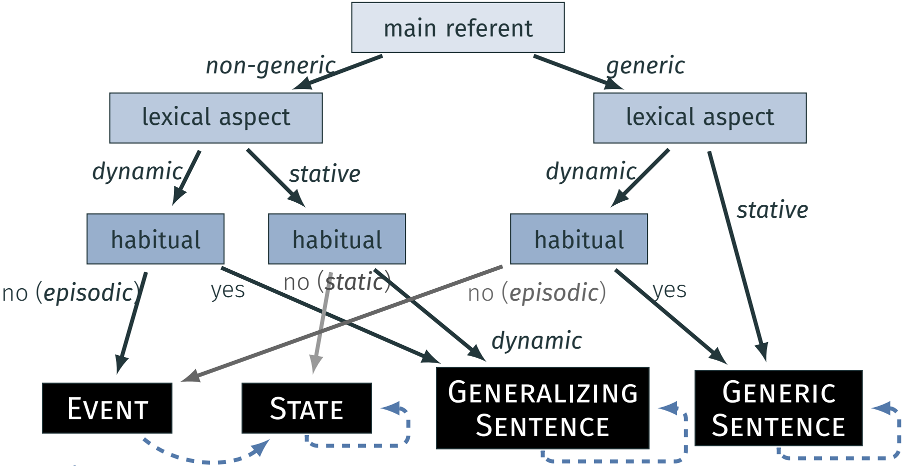
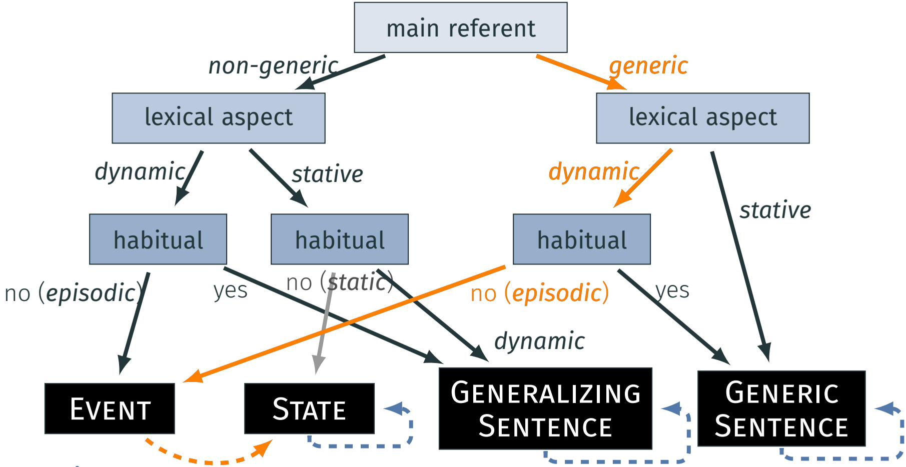


coercion: negation, modals, conditional, perfect, future

Annotation scheme

[Friedrich and Palmer, 2014b] [Friedrich et al., 2015]



coercion: negation, modals, conditional, perfect, future

The bicycle <u>had</u> <u>not</u> yet <u>been</u> invented in the 18th century.

Overview of thesis work

computational modeling

corpus creation / analysis of agreement

linguistic background / annotation scheme

generics
reference to kinds

[Friedrich & Pinkal, ACL 2015]
[Friedrich et al., LAW 2015]

lexical aspect
state vs. event

[Friedrich & Palmer, ACL 2014]

habituals
generalization
over situations

[Friedrich & Pinkal, EMNLP 2015]

situation entity types [Smith, 2003]

[Friedrich et al., ACL 2016], [Friedrich & Palmer, LAW 2014],
[Mavridou et al., LSDSem 2015], [Palmer & Friedrich, 2014]

Automatic prediction of lexical aspectual class

She **filled** the glass with water. (***dynamic***)
The glass **is filled** with water. (***stative***)

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MASC (jokes, news, letters) • 7875 clauses

Random Forest classifier [Breiman, 2001] with features:

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Finding #1: linguistic indicators generalize across verb types

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10-fold cross validation • verbs in test folds $\cap$ verbs in train fold $= \emptyset$

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Finding #2: contextual features help for ambiguous verb types

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generics	lexical aspect	habituals
reference to kinds	state vs. event	generalization over situations
[Friedrich & Pinkal, ACL 2015] [Friedrich et al., LAW 2015]	[Friedrich & Palmer, ACL 2014]	[Friedrich & Pinkal, EMNLP 2015]

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Automatic recognition of habituals

John bought a bike.	(***episodic***)
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Bill can cycle.

coercion to STATE:
negation, modality, future,
perfect, conditionality

Automatic recognition of habituals

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Wikipedia (10,355 clauses) • Random Forest classifiers [Breiman, 2001]

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Findings / contributions:

#1: recognizing ***habituals*** in free text
requires a **three-way distinction**

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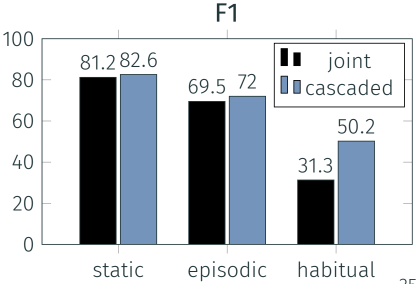
Findings / contributions:

- #1: recognizing ***habituals*** in free text requires a **three-way distinction**
- #2: **contextual** and **verb type-based features** are complementary
- #3: filtering out ***static*** clauses first is beneficial (**cascaded** model)



Linear-chain Conditional Random Field

probability of label sequence $\vec{y}$ given observation sequence $\vec{x}$

sum over observations in $\vec{x}$

sum over feature functions

$$P(\vec{y}|\vec{x}) = \frac{1}{Z(x)}\, exp\left(\sum_{j=1}^{N}\left[\sum_{i}\lambda_i f_i(y_{j-1}, y_j) + \sum_{k}\lambda_k f_k(x_j, y_j)\right]\right)$$

normalization over scores for all possible label sequences with length $|\vec{x}|$

λ: weights for feature functions (independent of position in sequence j)

discriminative training: CRF++ toolkit uses L-BGFS

main

References I

Bach, E. (1986).
The algebra of events.
Linguistics and philosophy, 9(1):5–16.

Becker, M., Staniek, M., Nastase, V., Palmer, A., and Frank, A. (2017).
Classifying semantic clause types: Modeling context and genre characteristics with recurrent neural networks and attention.
In *Proceedings of the 6th Joint Conference on Lexical and Computational Semantics (*SEM 2017)*, pages 230–240. Association for Computational Linguistics.

Breiman, L. (2001).
Random forests.
Machine learning, 45(1):5–32.

Brown, P. F., Desouza, P. V., Mercer, R. L., Pietra, V. J. D., and Lai, J. C. (1992).
Class-based n-gram models of natural language.
Computational linguistics, 18(4):467–479.

Dai, Z. and Huang, R. (2018).
Building context-aware clause representations for situation entity type classification.
In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP).*

Eckart de Castilho, R. and Gurevych, I. (2014).
A broad-coverage collection of portable NLP components for building shareable analysis pipelines.
In *Proceedings of the Workshop on Open Infrastructures and Analysis Frameworks for HLT*, pages 1–11, Dublin, Ireland.

Francis, W. N. and Kučera, H. (1979).
Brown corpus manual.
Brown University.
http://clu.uni.no/icame/brown/bcm.html.

References II

Friedrich, A. and Palmer, A. (2014a).
Automatic prediction of aspectual class of verbs in context.
In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (ACL)*, Baltimore, USA.

Friedrich, A. and Palmer, A. (2014b).
Situation entity annotation.
In *Proceedings of the 8th Linguistic Annotation Workshop (LAW VIII)*, Dublin, Ireland.

Friedrich, A., Palmer, A., and Pinkal, M. (2016).
Situation entity types: automatic classification of clause-level aspect.
In *In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (ACL)*, Berlin, Germany.

Friedrich, A., Palmer, A., Sørensen, M. P., and Pinkal, M. (2015).
Annotating genericity: a survey, a scheme, and a corpus.
In *Proceedings of the 9th Linguistic Annotation Workshop (LAW IX)*, Denver, Colorado, USA.

Friedrich, A. and Pinkal, M. (2015a).
Automatic recognition of habituals: a three-way classification of clausal aspect.
In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Lisbon, Portugal.

Friedrich, A. and Pinkal, M. (2015b).
Discourse-sensitive Automatic Identification of Generic Expressions.
In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics (ACL)*, Beijing, China.

Graff, D., Kong, J., Chen, K., and Maeda, K. (2003).
English Gigaword.
Linguistic Data Consortium, Philadelphia.

Hermes, J., Richter, M., and Neuefeind, C. (2015).
Automatic Induction of German Aspectual Verb Classes in a Distributional Framework.
In *Proceedings of the International Conference of the German Society for Computational Linguistics and Language Technology (GSCL)*, pages 122–129, Duisburg-Essen, Germany.

References III

Krifka, M., Pelletier, F. J., Carlson, G. N., ter Meulen, A., Link, G., and Chierchia, G. (1995).
Genericity: An Introduction.
In Carlson, G. N. and Pelletier, F. J., editors, *The Generic Book*, Studies in Communication, Media, and Public Opinion, pages 1–124. University Of Chicago Press.

Krippendorff, K. (1980).
***Content analysis: An introduction to its methodology*.**
Sage.

Loáiciga, S. and Grisot, C. (2016).
Predicting and using a pragmatic component of lexical aspect.
Linguistic Issues in Language Technology, Special issue on Modality in Natural Language Understanding, 13.

Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J., Bethard, S. J., and McClosky, D. (2014).
The Stanford CoreNLP Natural Language Processing Toolkit.
In *Proceedings of the 52nd annual meeting of the Association for Computational Linguistics (ACL) System Demonstrations*, pages 55–60, Baltimore, Maryland.

Mathew, T. A. and Katz, E. G. (2009).
Supervised Categorization of Habitual and Episodic Sentences.
In *Sixth Midwest Computational Linguistics Colloquium*, Bloomington, Indiana: Indiana University.

Mavridou, K.-I., Friedrich, A., Sorensen, M., Palmer, A., and Pinkal, M. (2015).
Linking discourse modes and situation entities in a cross-linguistic corpus study.
In *Proceedings of Linking Models of Lexical, Sentential and Discourse-level Semantics (LSDSem 2015)*, Lisbon, Portugal.

Nedoluzhko, A. (2013).
Generic noun phrases and annotation of coreference and bridging relations in the Prague Dependency Treebank.
In *Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse (LAW-VII)*, pages 103–111, Sofia, Bulgaria.

References IV

Palmer, A., Ponvert, E., Baldridge, J., and Smith, C. (2007).
A sequencing model for situation entity classification.
In *Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 896–903, Prague, Czech Republic.

Reichart, R. and Rappoport, A. (2010).
Tense sense disambiguation: a new syntactic polysemy task.
In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 325–334, Cambridge, Massachusetts, USA.

Reiter, N. and Frank, A. (2010).
Identifying generic noun phrases.
In *Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 40–49, Sweden, Uppsala.

Siegel, E. V. and McKeown, K. R. (2000).
Learning methods to combine linguistic indicators: Improving aspectual classification and revealing linguistic insights.
Computational Linguistics, 26(4):595–628.

Smith, C. S. (2003).
Modes of discourse: The local structure of texts.
Cambridge University Press.

Sonnenhauser, B. (2004).
Proceedings of the 2nd Workshop on Text Meaning and Interpretation, chapter Underspecification of 'meaning': The case of Russian imperfective aspect.

Soricut, R. and Marcu, D. (2003).
Sentence level discourse parsing using syntactic and lexical information.
In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology (NAACL-HLT)*, pages 149–156, Edmonton, Canada.

References V

Steedman, M. (2012).
Computational linguistics.
In Binnick, R. I., editor, *The Oxford handbook of tense and aspect*. Oxford University Press.

Turian, J., Ratinov, L., and Bengio, Y. (2010).
Word representations: a simple and general method for semi-supervised learning.
In *Proceedings of the 48th annual meeting of the Association for Computational Linguistics (ACL)*, pages 384–394, Uppsala, Sweden.

Van Durme, B. D. (2009).
Extracting implicit knowledge from text.
PhD thesis, University of Rochester.

Vendler, Z. (1957).
Verbs and times.
The philosophical review, pages 143–160.

Zarcone, A. and Lenci, A. (2008).
Computational models for event type classification in context.
In *Proceedings of The International Conference on Language Resources and Evaluation (LREC)*, Marrakech, Morocco.

Zhang, Y. and Xue, N. (2014).
Automatic Inference of the Tense of Chinese Events using Implicit Linguistic Information.
In *Proceedings of The Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Doha, Qatar.