CLUSTER OF EXCELLENCE

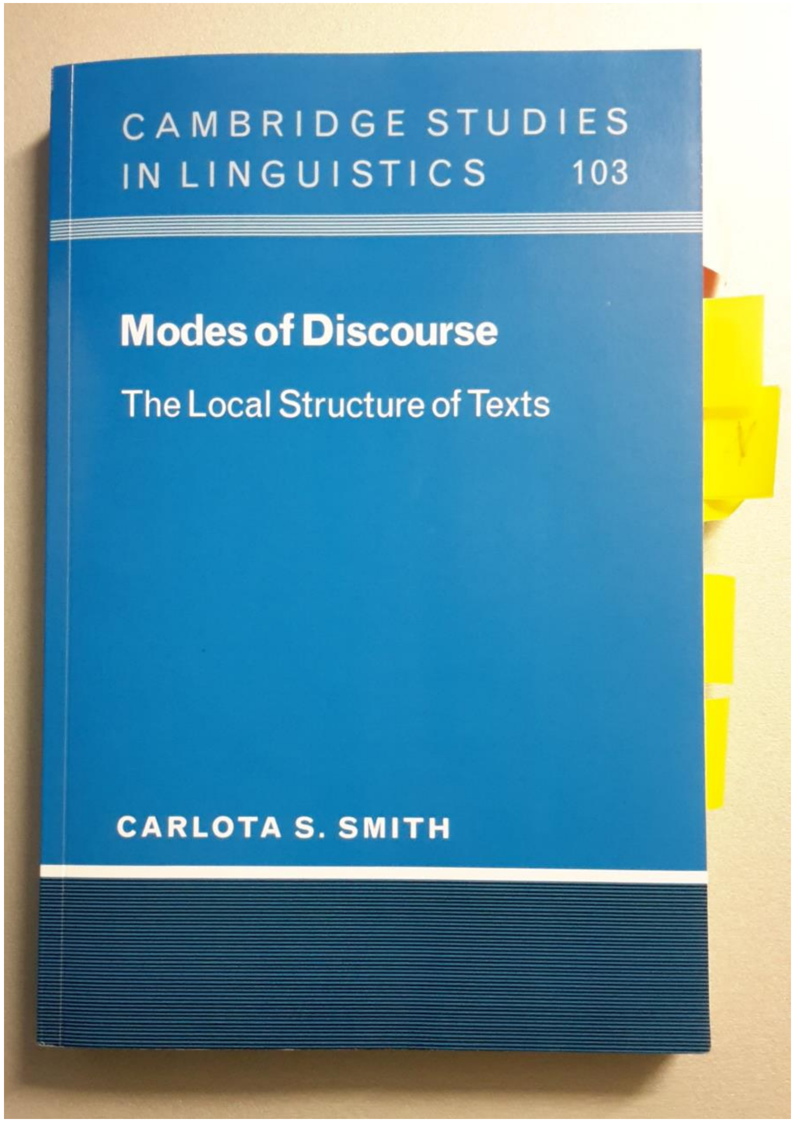
UNIVERSITÄT DES SAARLANDES

Annotation and automatic classification of situation entity types

Prague, November 2015

Annemarie Friedrich, Saarland University
joint work with Alexis Palmer and Manfred Pinkal

Carlota Smith: Modes of discourse (2003)



Thanks!

Alexis Palmer

Manfred Pinkal

Melissa
Peate
Sorensen

Liesa Heuschkel

Kleio-Isidora Mavridou

Christine
Bocionek

Fernando
Ardente

Ruth Kühn

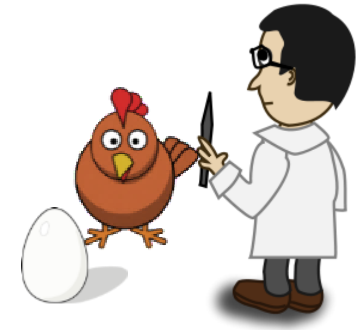
Ambika Kirkland

Damyana Gateva

Discourse modes

NARRATIVE

Prof. Dr. Origin at Saarland University came into his office one morning and was very surprised by the results of an experiment he had started the day before. He called in his assistants to inspect the hen and the egg that were the subject of his experiments…



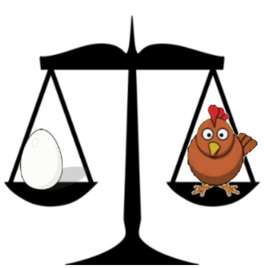
INFORMATION

The chicken or the egg causality dilemma is commonly stated as "which came first, the chicken or the egg?" To ancient philosophers, the question about the first chicken or egg also evoked the questions of how life and the universe in general began. …

ARGUMENT

COMMENTARY

In my opinion, the results of Prof. Dr. Origin's group are highly interesting, but they do by no means solve the philosophical question of how life and the universe began. I believe that much more research is needed, and that the field of biology alone will not be able to answer this question.



one text

≈ one genre

one passage

≈ one discourse mode

Discourse modes & situation entity types

Prof. Dr. Origin at Saarland University **came into his office** one morning and **was very surprised** by the results of an experiment he **had started** the day before. He **called** in his assistants to inspect the hen and the egg that **were the subject** of his experiments…

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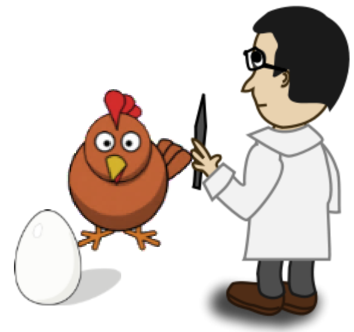


NARRATIVE

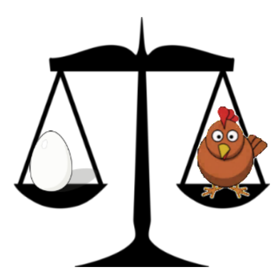
STATE

EVENT

INFORMATION

GENERIC SENTENCE

GENERALIZING SENTENCE



ARGUMENT COMMENTARY

STATE, EVENT, ABSTRACT ENTITIES, GENERIC / GENERALIZING SENTENCES

Discourse modes & type of progression

Prof. Dr. Origin at Saarland University **came into his office** one morning and **was very surprised** by the results of an experiment he **had started** the day before. He **called** in his assistants to inspect the hen and the egg that **were the subject** of his experiments…

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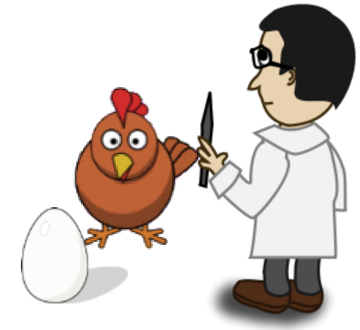
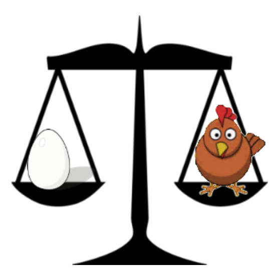


NARRATIVE

temporal
situations related to one another

INFORMATION

metaphorical
through domain

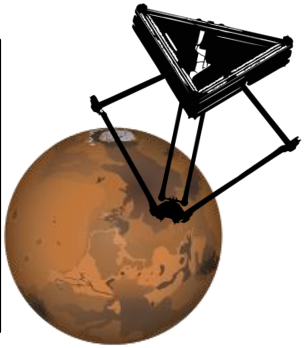


ARGUMENT
COMMENTARY

metaphorical

Additional discourse modes [Smith 2003]

On Monday, NASA **announced** that signs of liquid water **have been found** on Mars. The Mars Reconnaissance Orbiter spacecraft **found** evidence of the liquid on the Martian surface, in long dark spots on the Red Planet thought to be formed because of water flow.



REPORT

STATE, EVENT

temporal progression related to speech time.

The sand-hills here run down to the sea, and end in two spits of rock jutting out opposite each other, till you lose sight of them in the water. One is called the North Spit, and one the South.

DESCRIPTION

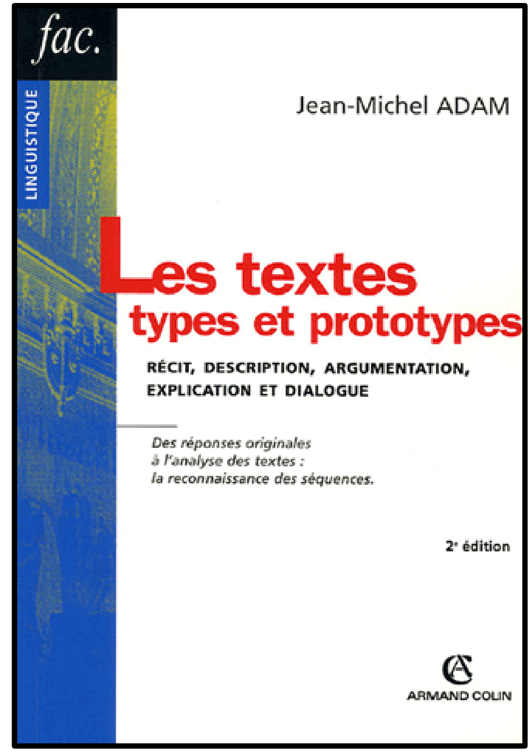
STATE, on-going EVENT

metaphorical progression through scene

Discourse modes: related theories

Egon Werlich, 1989

text types
narration, description, exposition, argumentation, instruction



Jean-Michel Adam, 2005

typical sequences
narrative, argumentative, descriptive, explicative, dialogued

Discourse modes: relevance for NLP

- temporal discourse processing
  - knowing a passage's discourse mode is a necessary prerequisite for interpreting tense [Smith 2005]
- automatic summarization, information extraction
  - focus on information in particular passages depending on the mode; user-specific summarization
- argumentation mining
  - narrow the search space for claims by focusing on argumentative passages
- genre distinctions
  - literary studies

Situation entity types

situations / eventualities
≈ evoked by finite clauses

1. Yesterday, Mary bought a cat. **EVENT**
2. Now she owns four cats. **STATE**
3. Susie often feeds Mary's cats. **GENERALIZING SENTENCE**
4. Cats are very social animals. **GENERIC SENTENCE**

More situation entity types

ABSTRACT ENTITIES
here: clausal complements

frequent in ARGUMENT/COMMENTARY discourse mode

Susie **knows** — **STATE**

that Mary loves her cats a lot. — **FACT**

object of knowledge

Susie **believes** — **STATE**

that the cats also love Mary. — **PROPOSITION**

object of belief

Have you seen my cats? — **QUESTION**

Don't forget to feed the cats! — **IMPERATIVE**

[Palmer et al. 2007]

Situation entity types: summary

Eventualities	STATE	Mary likes cats.
	EVENT	Mary fed the cats.
	- REPORT	..., Mary said.
General Statives	GENERALIZING SENTENCE	Mary often feeds my cats.
	GENERIC SENTENCE	Cats are always hungry.
Abstract Entities	FACT	I know that Mary fed the cats.
	PROPOSITION	I believe that Mary fed the cats.
Speech Acts	QUESTION	Does Mary like cats?
	IMPERATIVE	Don’t forget to feed the cats!

Situation entity types: summary

Eventualities	STATE	Mary likes cats.
	EVENT	Mary fed the cats.
	- REPORT	..., Mary said.
General Statives	GENERALIZING SENTENCE	[illegible] cats.
	GENERI[illegible] SENT[illegible]	[illegible]
Abstract [illegible]	FACT	[illegible]
	PROPOS[illegible]	[illegible]
[illegible]	QUE[illegible]	[illegible]
	IMPERATIVE	Don't forget to feed the cats!

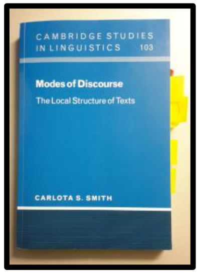
Writer / speaker chooses how to present things:

The ship was in motion. STATE

The ship moved. EVENT

Carlota Smith: The Parameter of Aspect (1997).

Situation entity annotation



Carlota Smith: Modes of Discourse (2003).

Many examples, but no formal definition of the different situation entity types.

Alexis Palmer, Elias Ponvert, Jason Baldridge, and Carlota Smith.
A sequence model for situation entity classification. ACL 2007.

- first labeled data set for SEs, ~6000 clauses
- no annotation manual, Cohen's κ = 0.54

convey **annotation scheme +** **delines** to notators

What are the **most importan** **differences** between Smith's situation entity types?

Annemarie Friedrich and Alexis Palmer.
Situation entity annotation. LAW 2014.

Situation entity types: feature-based annotation

What are the **main differences** between the different situation entity types?

Does the verb express an **event** or a **state**?

aspectual class

Does something happen repeatedly or once?

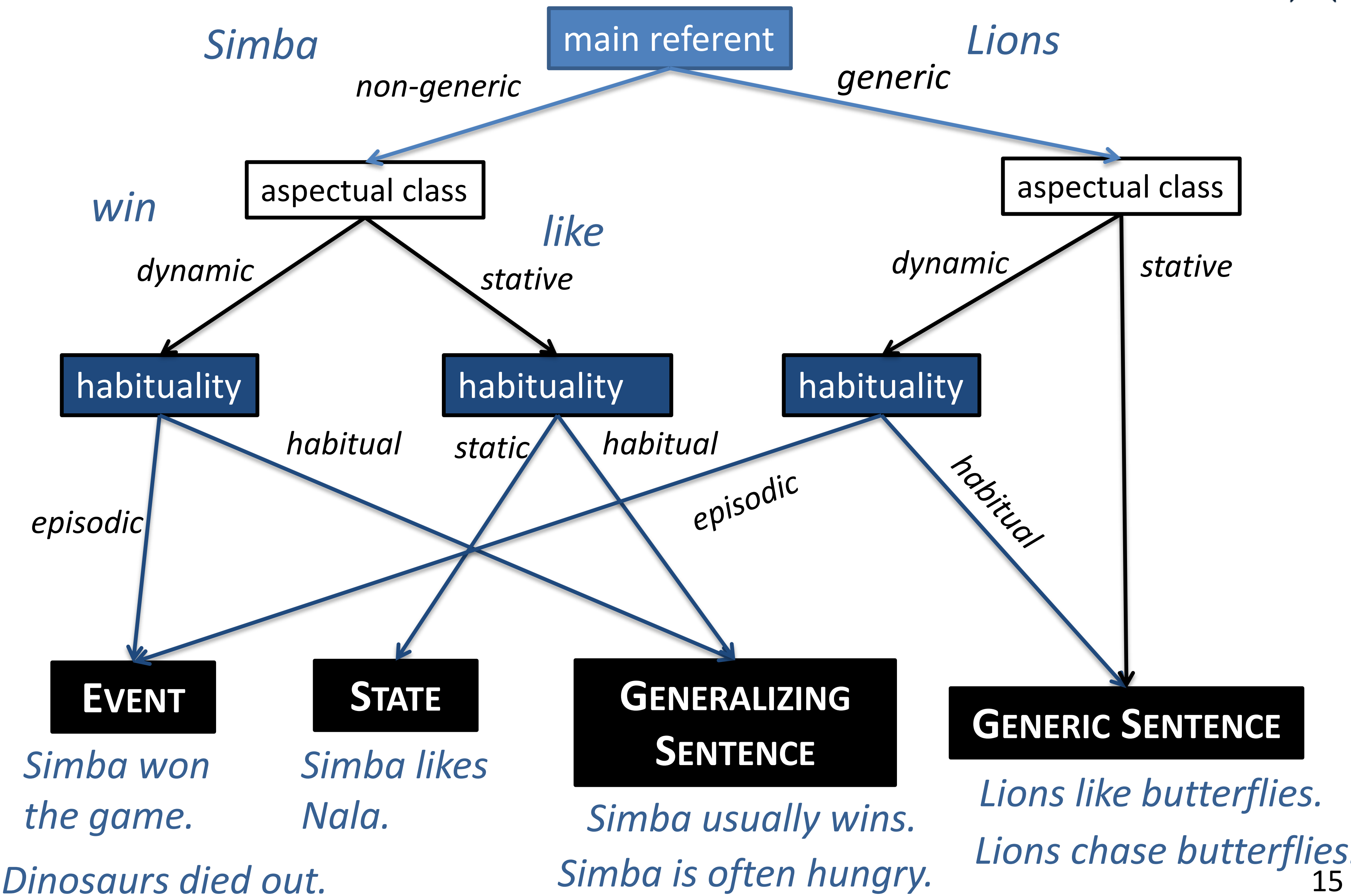
habituality

Does the sentence talk about a **particular referent** or a **kind/class**?

genericity

		Mary likes cats
		Mary fed the c
	- REPORT	..., Mary said.
		Mary often feeds r cats.
		Cats are always hungry.
		I know that Mary fed the cats.
Entities	PROPOSITION	I believe that Mary fed the cats.
Speech Acts	QUESTION	Does Mary like cats?
	IMPERATIVE	Don't forget to feed the cats!

A decision tree for labeling situation entities



Situation entity types: coercion

some linguistic phenomena coerce **EVENTs** to **STATEs**:

negation, modality, future / perfect,
conditionality, subjectivity

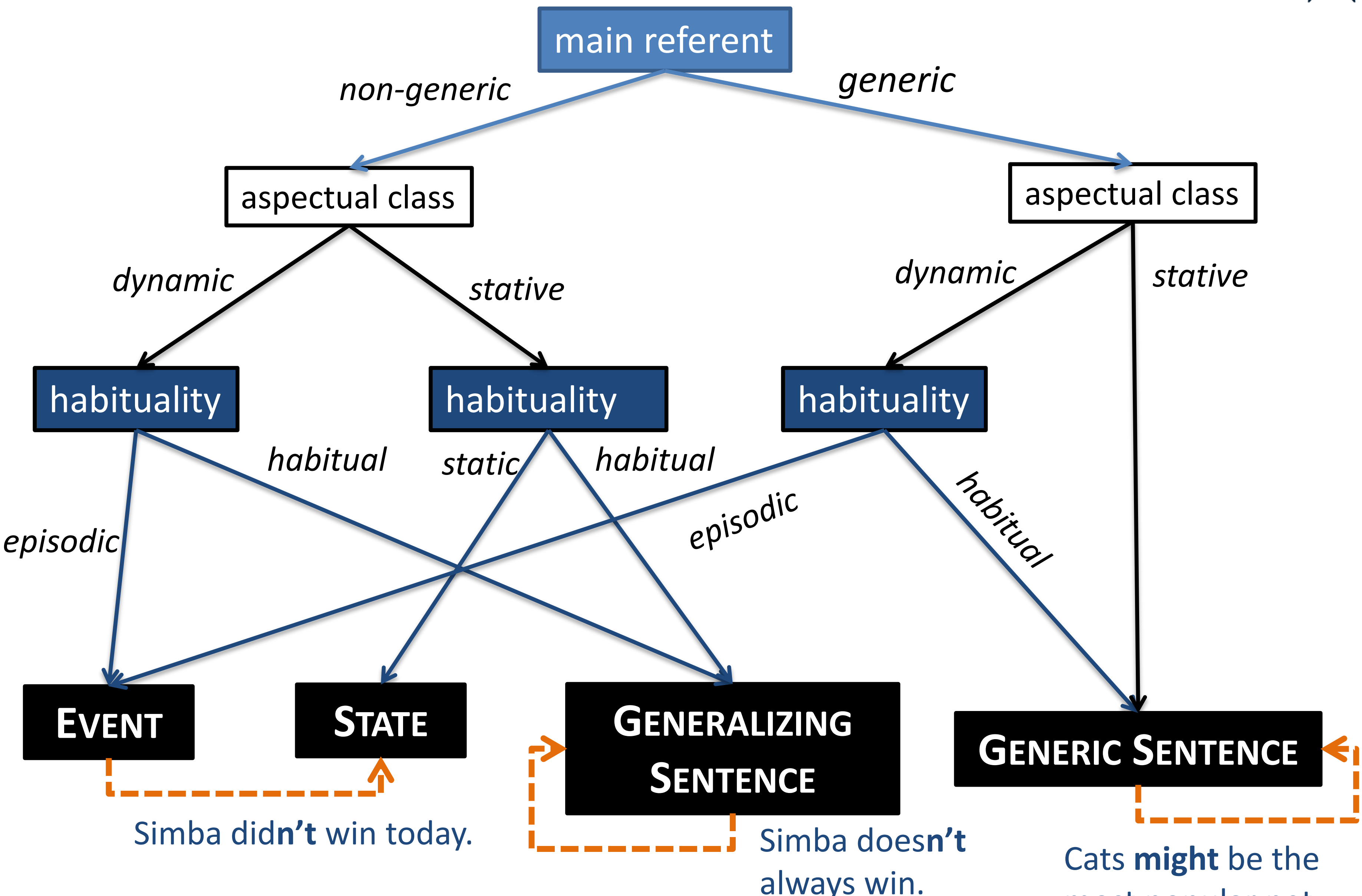
Susie will feed the cats.
Susie has not fed the cats.
If Susie has forgotten the cats,
they might be hungry now.

does not apply to general statives:

Susie never feeds Mary’s cats. GENERALIZING SENTENCE

Cats might be the most popular pet. GENERIC SENTENCE

A decision tree for labeling situation entities



negation, modals, conditional, perfect, future

Data sets and annotation procedure

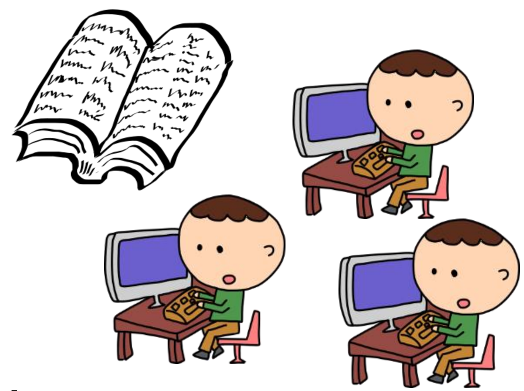
MASC
25,000 clauses
essays, letters, fiction, technical, travel, news …

Wikipedia
10,000 clauses
botany, animals, sports, biographies, science, …

segmentation into clauses (SPADE)

Annotators label
- situation entity type
- genericity of main referent
- lexical aspectual class of main verb
- habituality of main verb

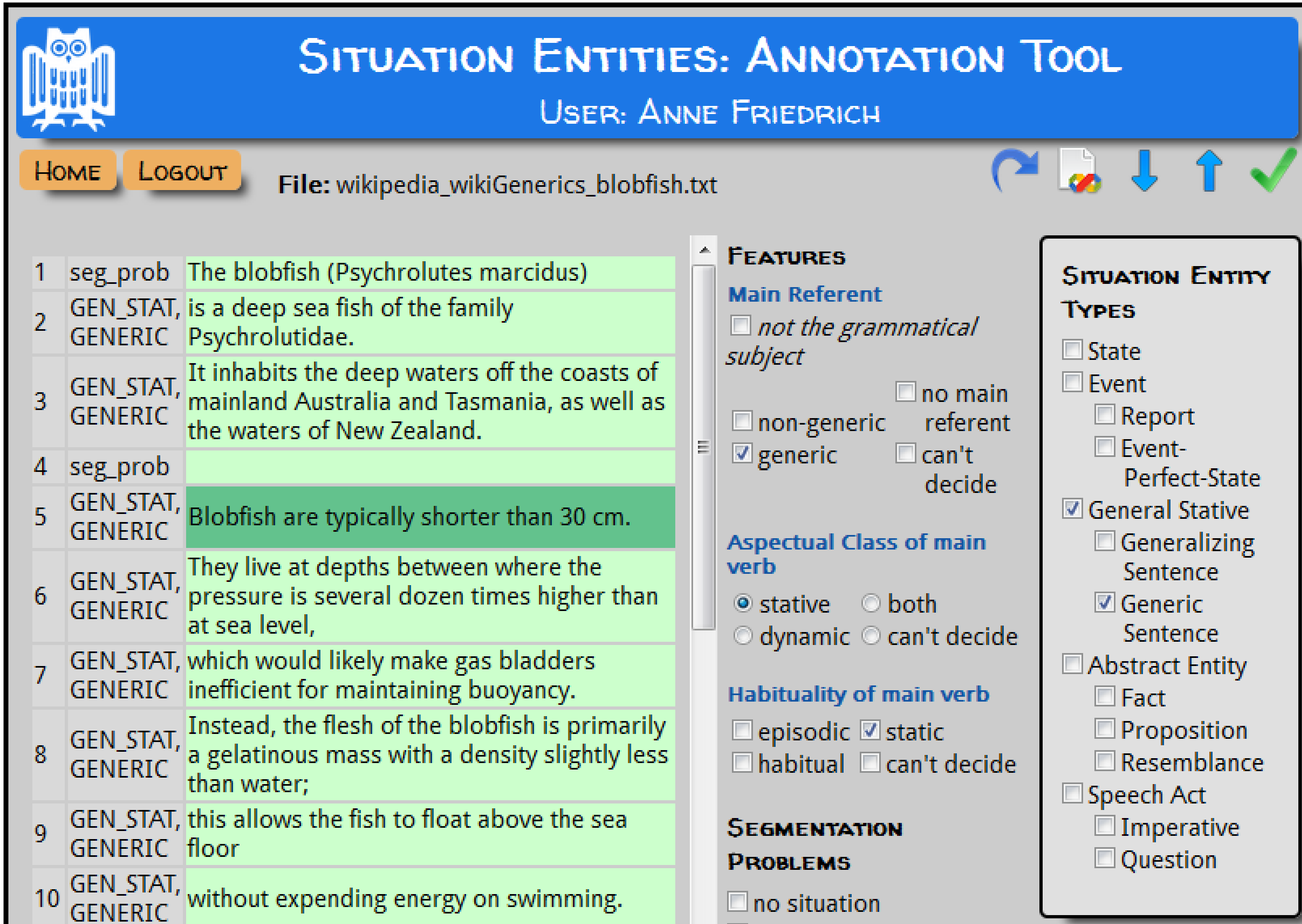
training phase
+ manual



gold standard = majority vote over labels of 3 annotators

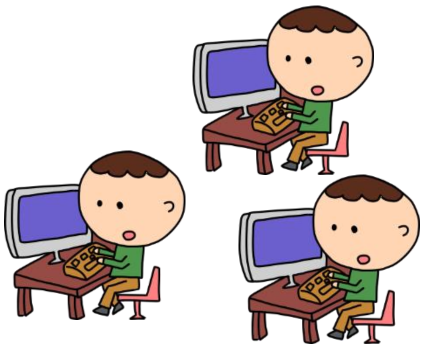
(about 10% of segments marked as "NO SITUATION")

Annotation of situation entity types and features



Inter-annotator agreement

Wikipedia data
(MASC is in progress)

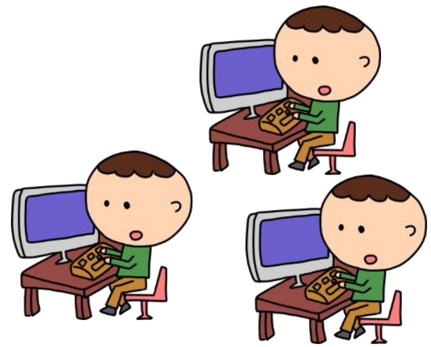


Fleiss' κ

Fleiss' κ: features		
aspectual class	stative, dynamic, both	0.65
main referent	generic, non-generic, cannot decide	0.70
habituality	episodic, static, habitual, cannot decide	0.61

Inter-annotator agreement

Wikipedia data
(MASC is in progress)



Fleiss' κ

Susie **believes** STATE
that the cats also love Mary. PROPOSITION, STATE

Krippendorff's diagnostics

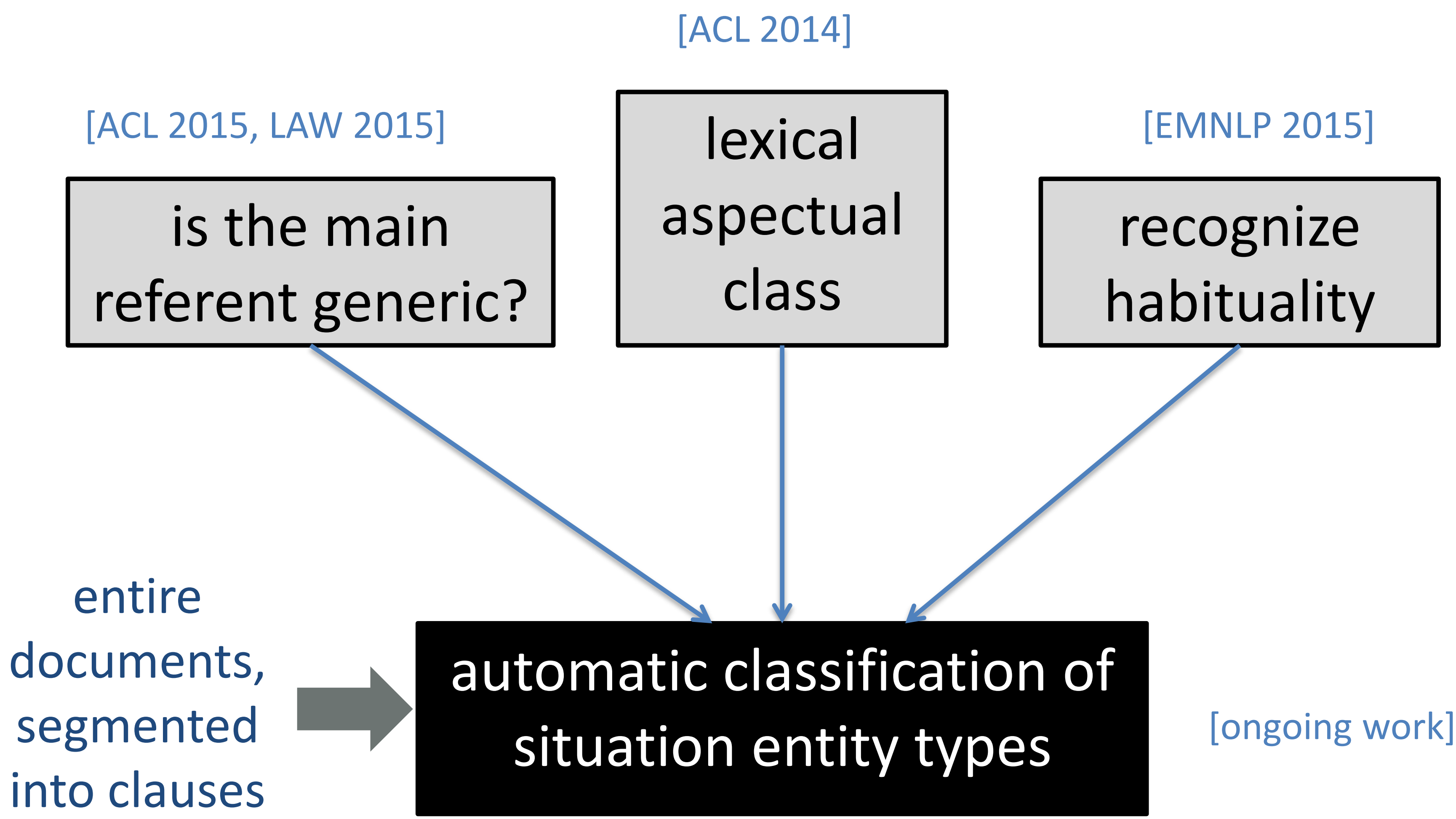
Higher-level types	
CATEGORY	Fleiss' κ
all categories	**0.67**
eventuality	0.69
general statives	0.69
abstract entities	0.19
speech acts	0.85

Basic-level types	
CATEGORY	Fleiss' κ
all categories	**0.65**
STATE	0.58
EVENT	0.74
GENERIC SENTENCE	0.71
GENERALIZING SENTENCE	0.35
SPEECH ACT	0.85

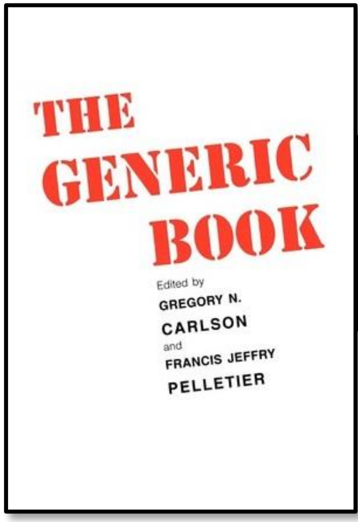
Situation entity types: relevance for NLP

- identifying the discourse modes of a text passage
- corpus data and computational models for sub-tasks studied in the NLP community for which no large data sets are available
  - automatic classification of fundamental aspectual class [Siegel & McKeown 2000, Friedrich & Palmer 2014] with the aim of improving temporal discourse processing [UzZaman et al. 2013, Bethard 2013, Costa & Branco 2012]
  - identifying generic noun phrases [Reiter & Frank 2013]
  - identifying habitual vs. episodic sentences [Mathew & Katz 2009]

Computational modeling of situation entity types

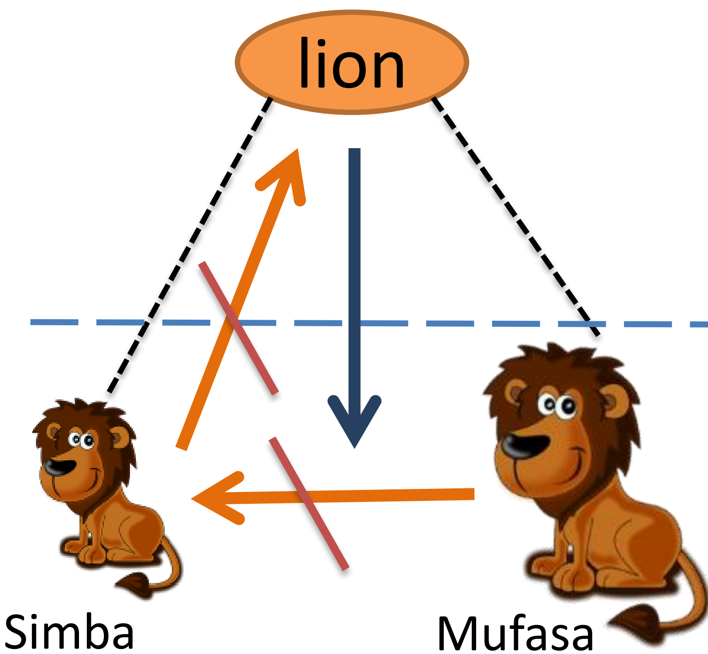


Genericity



Krifka, Manfred, et al.
Introduction to genericity.
In *The Generic Book* (1995).

- ✓ information / event extraction
- ✓ knowledge acquistion from text



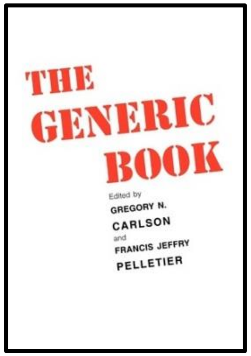
different
entailment properties

<u>Lions</u> are dangerous.

kind-referring generic

<u>Mufasa</u> is dangerous.
<u>Simba</u> is dangerous.

non-generic



Reference to kinds

form of NP not sufficient

	kind-referring	non-kind-referring
definite NPs	The lion is a predatory cat.	The cat chased the mouse.
indefinite NPs	Lions eat meat.	Dogs were barking outside.
quantified NPs	Some (type of) dinosaur is extinct.	Some dogs were barking outside.
proper names	Panthera leo persica was first described by the Austrian zoologist Meyer.	John likes ice cream.

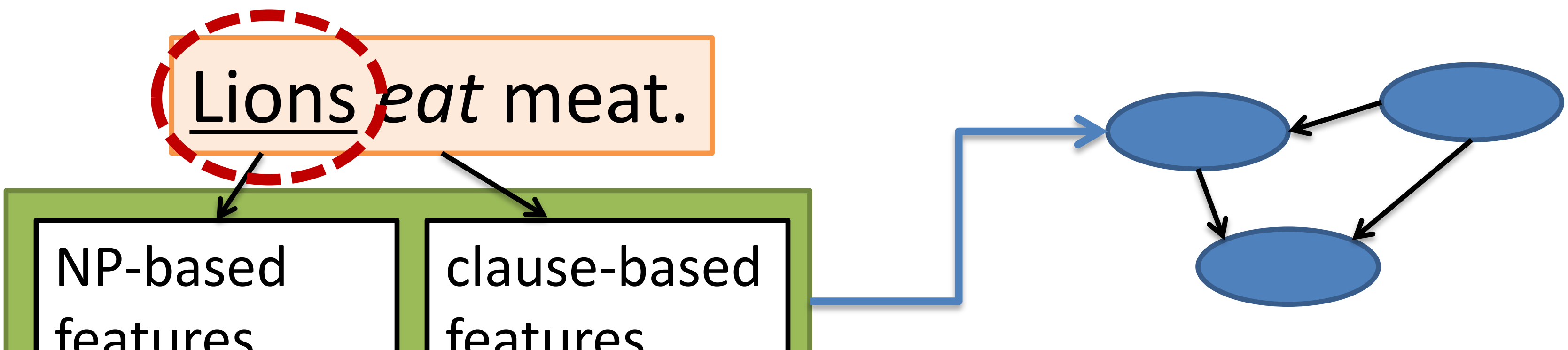
clause / context matters

Baseline: identifying generic noun phrases

Data: ACE-2 & ACE-2005

→ largest corpora annotated with NP-level genericity to date, ~40k NPs

- SPC = specific / non-generic
- GEN = generic
- USP = underspecified



Bayesian network [Weka]

Nils Reiter and Anette Frank. **Identifying generic noun phrases.** ACL 2010.

Syntactic-semantic features

→ reimplementation of R&F using freely available resources
→ extracted from dependency parses (Stanford parser)
https://github.com/annefried/sitent

NP-based features	
number	sg, pl
person	1,2,3
countability	Celex: count, uncount,…
noun type	common, proper, pronoun
determiner type	def, indef, demon
part-of-speech	POS of head
bare plural	true, false
WordNet based features	senses, lexical filename,…

Clause-based features	
dependency relations	between (subject) head and governor etc.
tense	past, present, future
progressive	true, false
perfective	true, false
voice	active, passive
part-of-speech	POS of head
temporal modifier	true, false
number of modifiers	numeric
predicate	lemma of head
adjunct-degree	positive, comparative, superlative

Discourse-sensitive approach

WIKIPEDIA
The Free Encyclopedia

[**Sugar maples**$_{\text{generic}}$] also have a tendency to color unevenly in fall.
[**The recent year's growth twigs**$_{\text{generic}}$] are green and turn dark brown.

genericity labeling of noun phrases in entire texts
→ sequence labeling task

Annemarie Friedrich and Manfred Pinkal. **Discourse-sensitive automatic identification of generic expressions.** ACL 2015.

Computational model for genericity

Sugar maples also have a tendency to color unevenly in fall.

The recent year's growth twigs are green.

sequence of clauses (entire document)

barePlural=true : 1
determinerType=def : 0
tense=present : 1
voice=active : 1
…

barePlural=true : 0
determinerType=def : 1
tense=present : 1
voice:active : 1
…

features: indicator functions

CRF

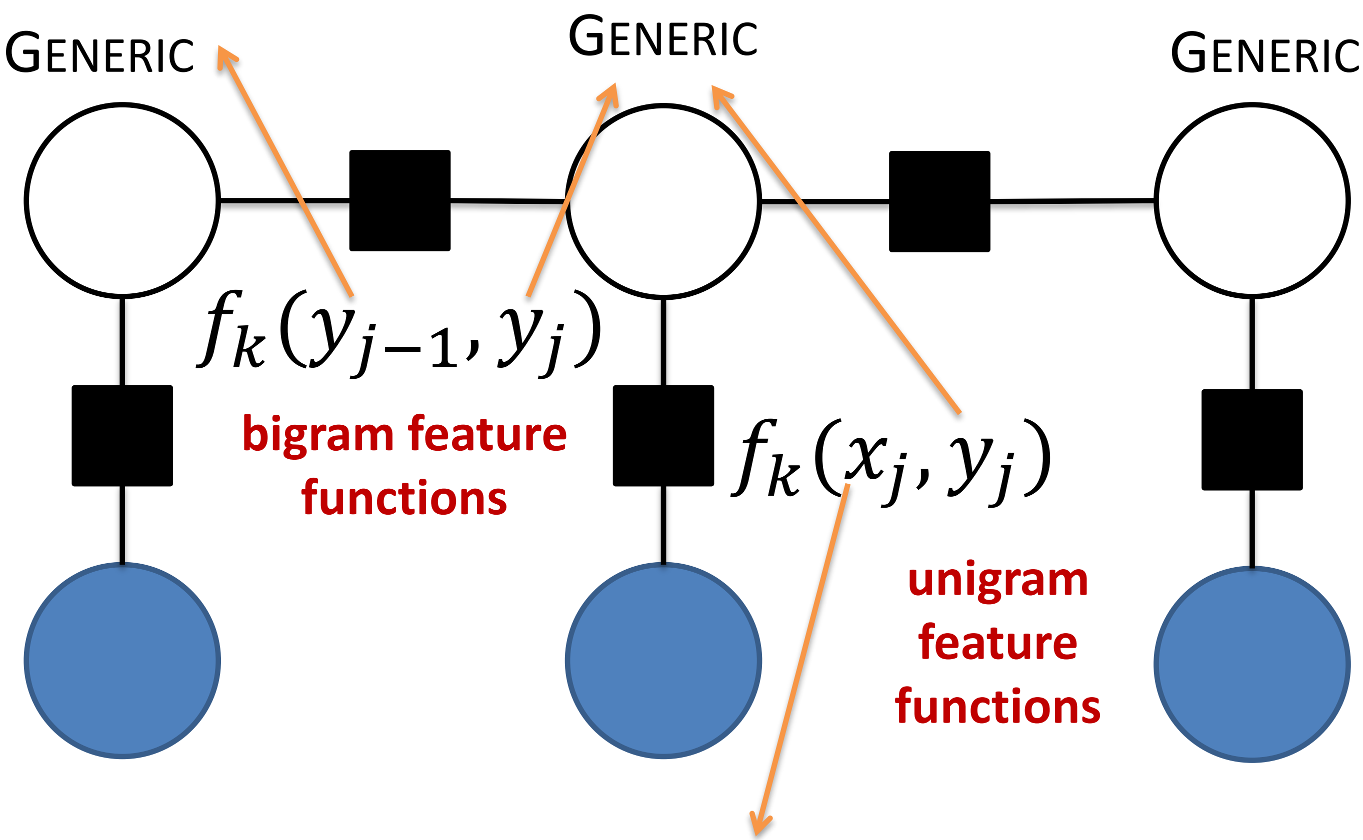
GENERIC

GENERIC

sequence of labels

Conditional random field (CRF)

CRF++
https://taku910.github.io/crfpp/



label sequence $\vec{y}$

$$P(\vec{y}|\vec{x}) \sim \sum_k \lambda_k f_k$$

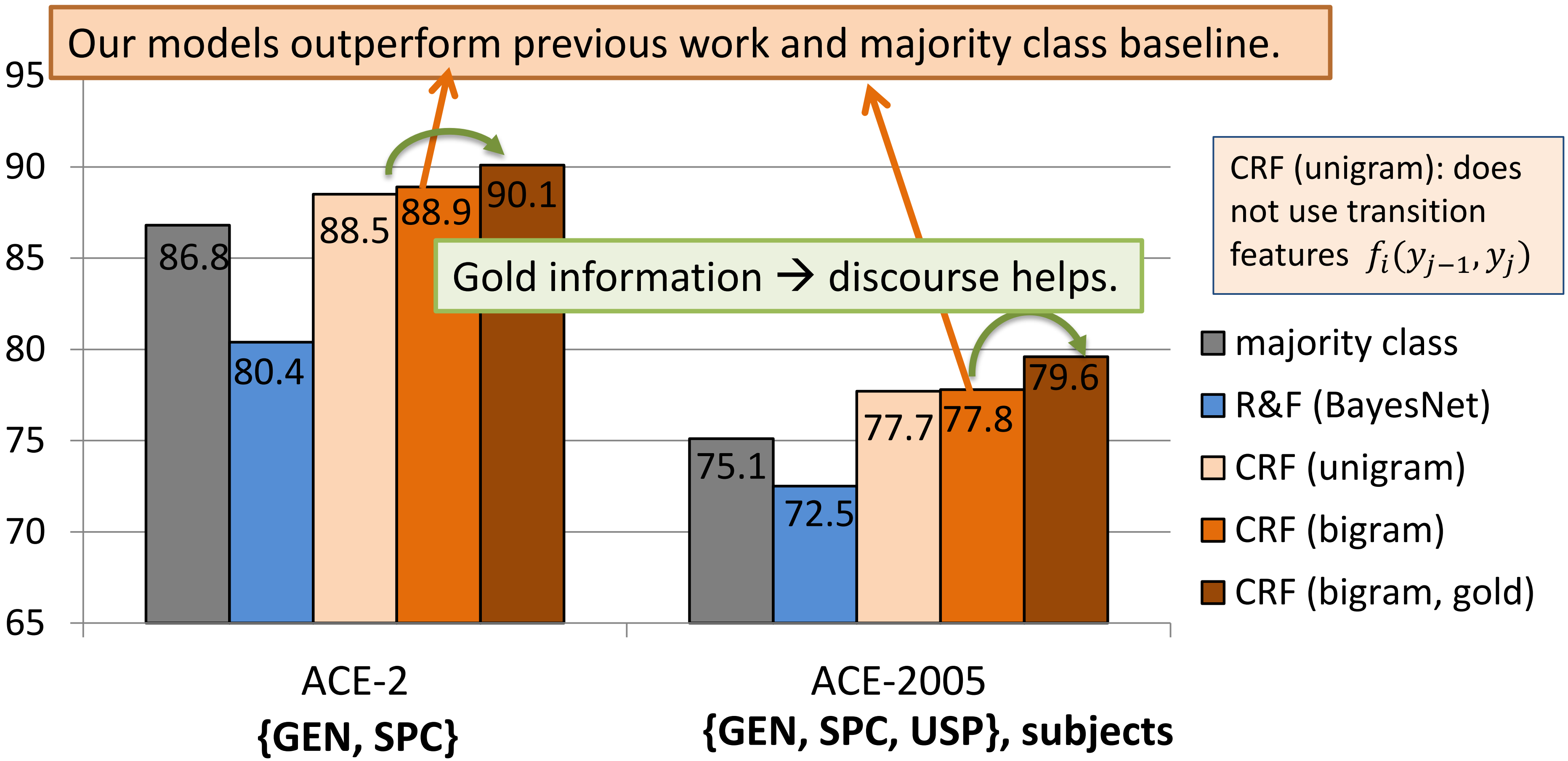
observation sequence $\vec{x}$

<u>Acer saccharum</u> is a deciduous tree.

<u>Sugar maples</u> also have a tendency to color unevenly in fall.

<u>The recent year's growth twigs</u> are green.

Accuracy: ACE-2 and ACE-2005

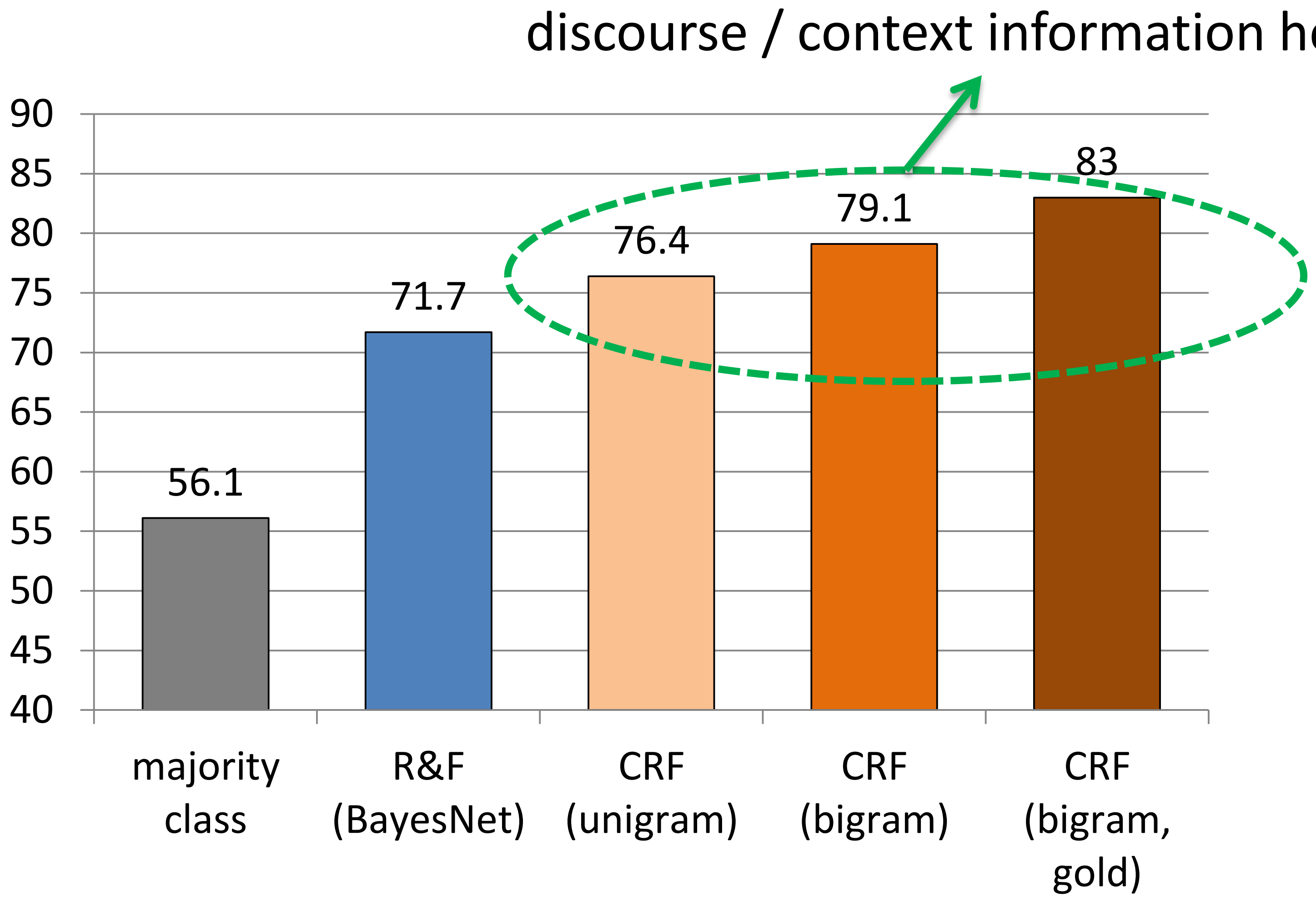


Few generic instances. (for details see Friedrich et al. (LAW 2015))

Problems in annotation guidelines, mix genericity and specificity.

→ *Officials reported…* (USP) → is non-generic, non-specific! → SPC

Accuracy: Wikipedia data (main referent)



all differences statistically significant

Computational modeling of situation entity types

[ACL 2014]

[ACL 2015, LAW 2015]

is the main referent generic?

lexical aspectual class

[EMNLP 2015]

recognize habituality

entire documents, segmented into clauses

automatic classification of situation entity types

[ongoing work]

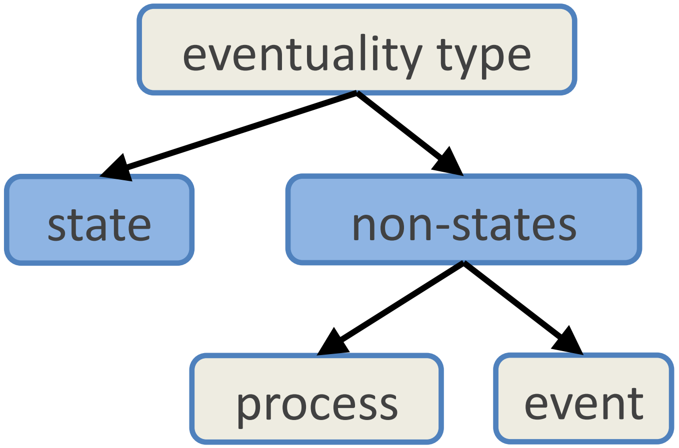
Lexical aspectual class

She **filled** the glass with juice.
dynamic

Juice **fills** the glass.
stative

The glass **was filled** with juice.
both interpretations possible

Bach [1986]: time schemata of <u>sentences</u>



Vendler [1957]: time schemata of <u>verbs</u>
lexical aspect / aktionsart

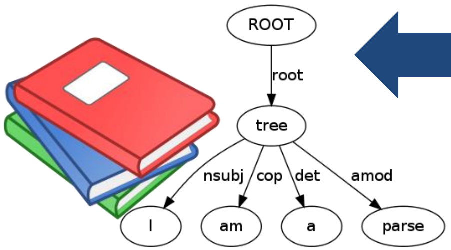
states	*love, own*	**stative**
activities	*run*	
accomplishments	*write a letter*	**dynamic**
achievements	*realize*	

Predicting fundamental lexical aspectual class

John will **love** this cake!	**stative**	*John love cake*
John has **kissed** Mary.	**dynamic**	*John kiss Mary*
John **drives** to work.	**dynamic**	*John drive to work*

Linguistic indicators

large parsed text corpus (Gigaword)



counts for each **verb type**

frequency	negated	no subject
present	perfect	evaluation adverb
past	progressive	continuous adverb
future	for-PP	manner adverb
particle	in-PP	temporal adverb

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

→15 features for each **verb type**

Eric Siegel and Kathleen McKeown. **Learning methods to combine linguistic indicators.** *Computational Linguistics*, 2000.

Fundamental lexical aspectual class

Eric Siegel and Kathleen McKeown, 2000.

Classification always results in majority class of verb type. Dataset not available.

The glass is **filled** with juice.

She **filled** the glass with juice.

<u>linguistic indicator features for **fill**:</u>

present	0.0927
negation	0.00024
…	…

<u>instance-based features for clause:</u>

tense	past
subject	noun.person
voice	active
…	…

Random Forest classifier

<u>training</u>: <u>labeled data</u>

She **likes** flowers. **stative**

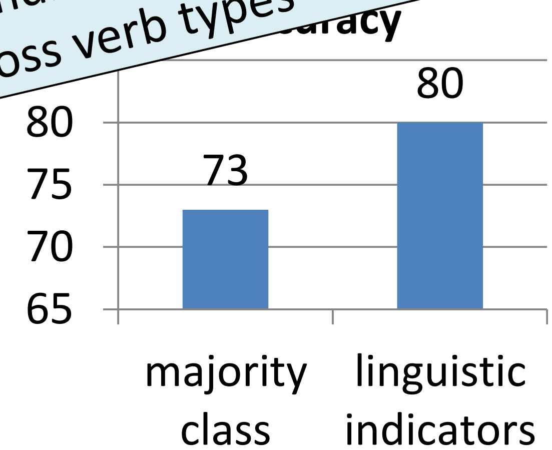
Mary **bought** a cat. **dynamic**

~6000 clauses from MASC, complete texts, κ=0.7

dynamic

linguistic indicators generalize across verb types

10-fold validation: UNSEEN VERBS



Annemarie Friedrich and Alexis Palmer. **Automatic prediction of aspectual class of verbs in context.** ACL 2014.

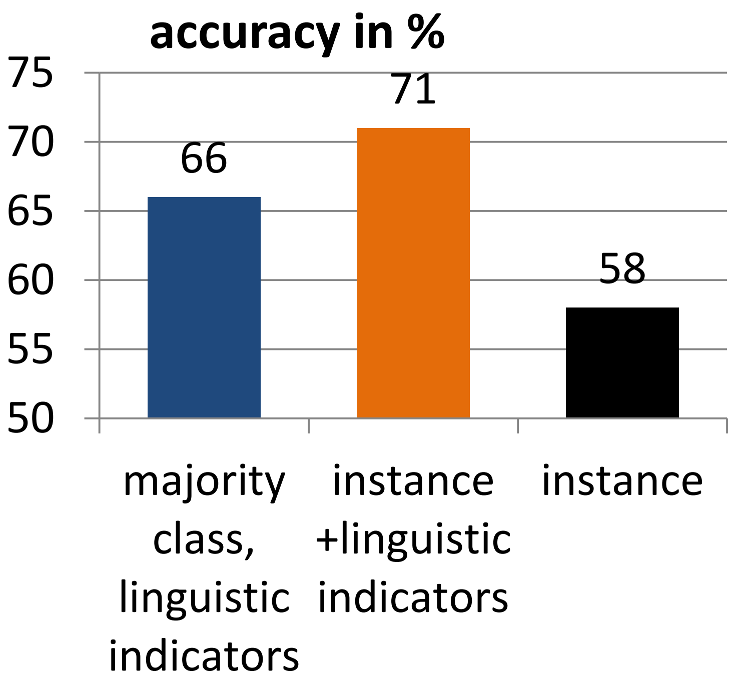
Prediction of aspectual class in context

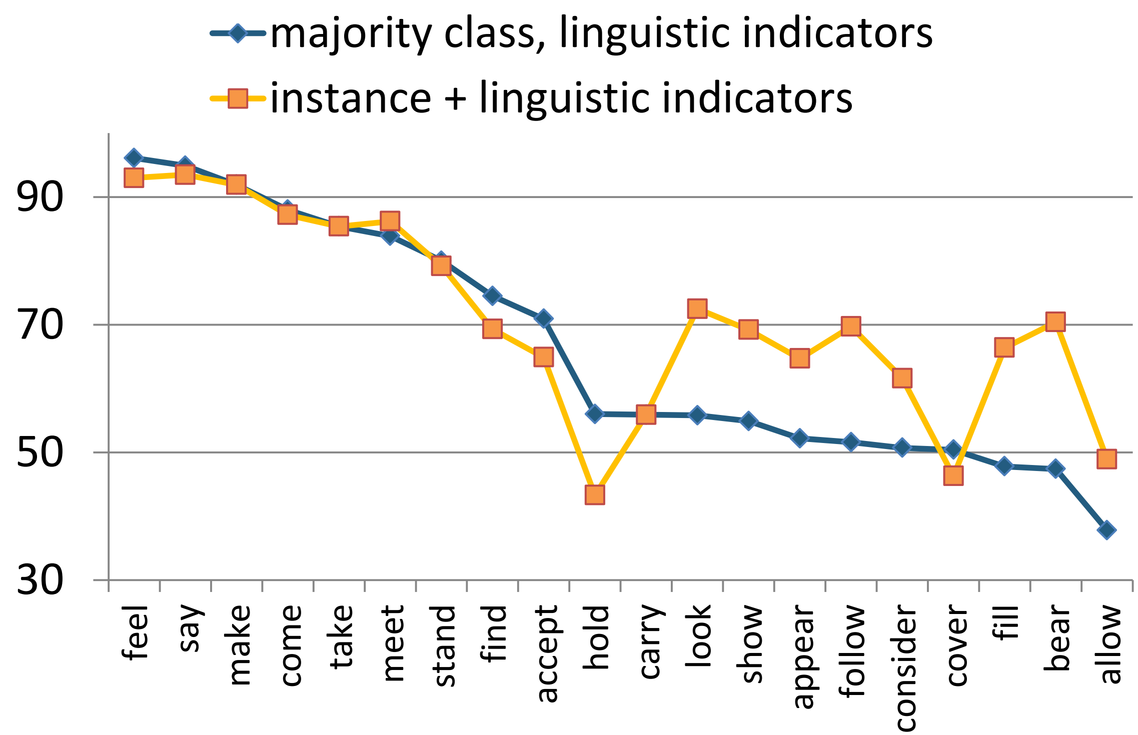
2667 sentences from Brown corpus for 20 frequent ambiguous verbs

2 annotators, κ = 0.6

Leave-One-Out CV

Annemarie Friedrich and Alexis Palmer. **Automatic prediction of aspectual class of verbs in context.** ACL 2014.





instance-based features do not generalize across verb types, but lead to improvement over type-based features

the more ambiguous the verb type, the more important the instance-based features

Computational modeling of situation entity types

[ACL 2014]

[ACL 2015, LAW 2015]

is the main referent generic?

lexical aspectual class

[EMNLP 2014]

recognize habituality

entire documents, segmented into clauses

automatic classification of situation entity types

[ongoing work]

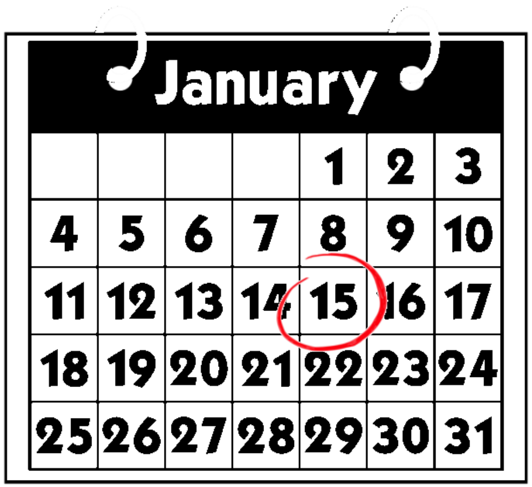
Habituality

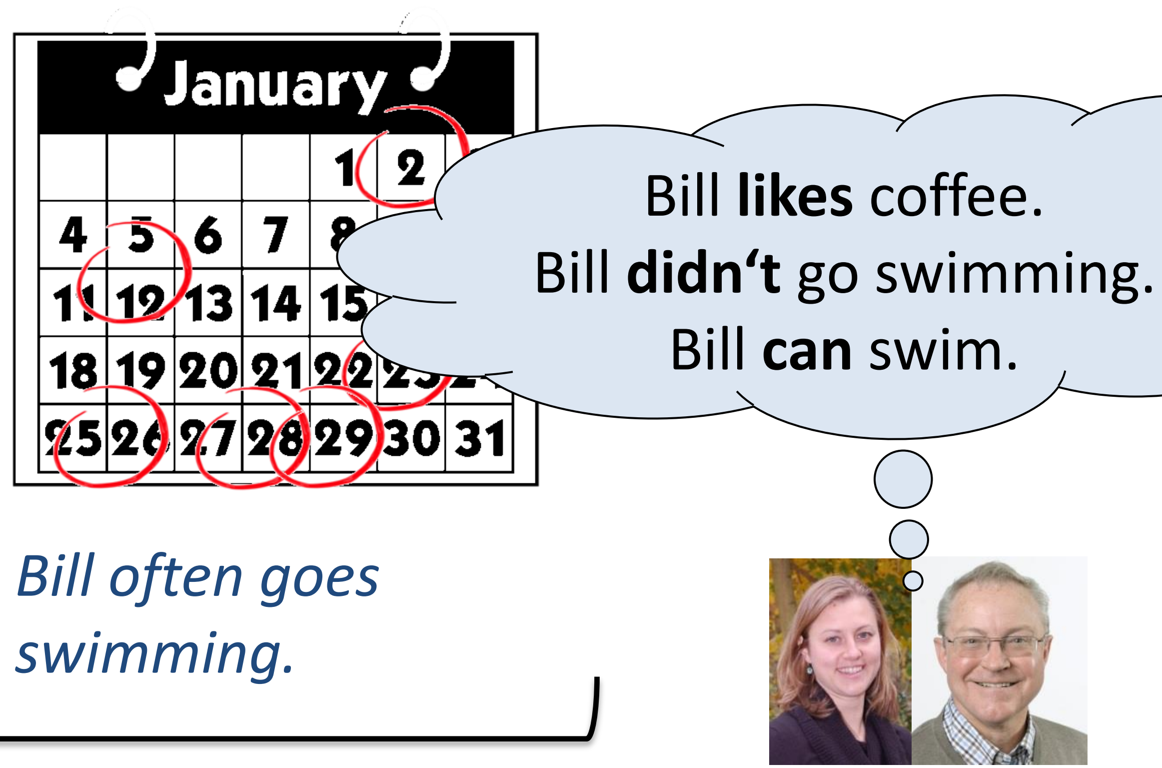
episodic

a particular event

habitual

generalization over situations,
exceptions are tolerated





John went swimming yesterday!

Bill often goes swimming.

Thomas Mathew and Graham Katz. **Supervised categorization of habitual and episodic sentences.** *Sixth Midwest Computational Linguistics Colloquium, Bloomington, Indiana*. 2009.

A three-way classification of clausal aspect

clausal aspect		**lexical aspect**
episodic	Bill **drank** a coffee after lunch.	*dynamic*
habitual	Bill *usually* **drinks** coffee after lunch.	*dynamic*
	Italians **drink** coffee after lunch.	*dynamic*
	Sloths *sometimes* **sit** on top of branches.	*stative*
	John *never* **drinks** coffee.	*dynamic*
static	Bill **likes** coffee.	*stative*
	Bill *can* **swim**.	*dynamic*
	Bill *didn't* **drink** coffee yesterday.	*dynamic*
	Mary *has* **made** a cake.	*dynamic*

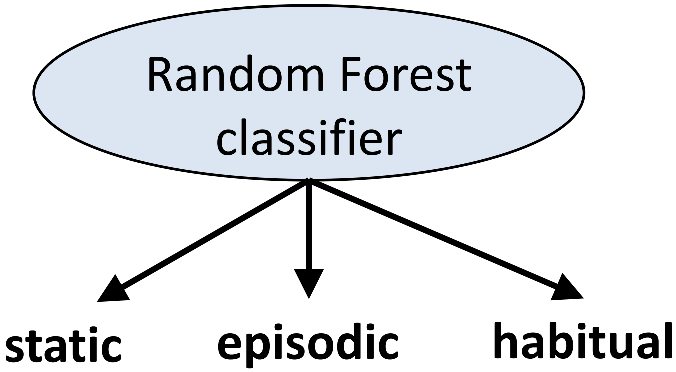
Annemarie Friedrich and Manfred Pinkal. **Recognising habituals: a three-way classification of clausal aspect.** EMNLP 2015.

Automatic classification of clausal aspect

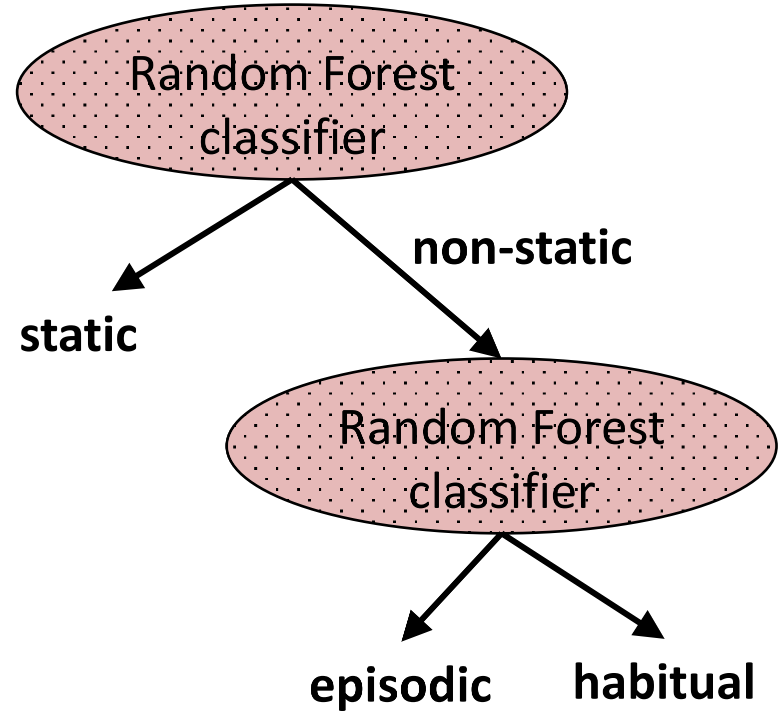
Features:

- instance-based features
- type-based features (linguistic indicators)

Joint Model



Cascaded Model



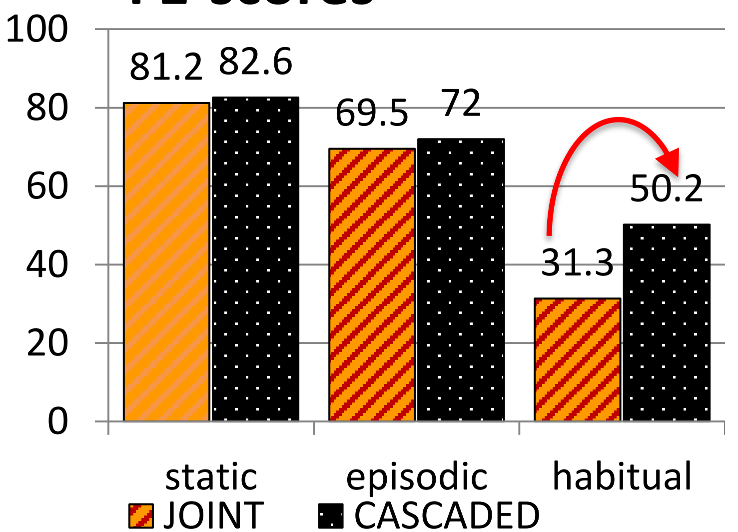
Annemarie Friedrich and Manfred Pinkal. **Recognising habituals: a three-way classification of clausal aspect.** EMNLP 2015.

Automatic classification of clausal aspect

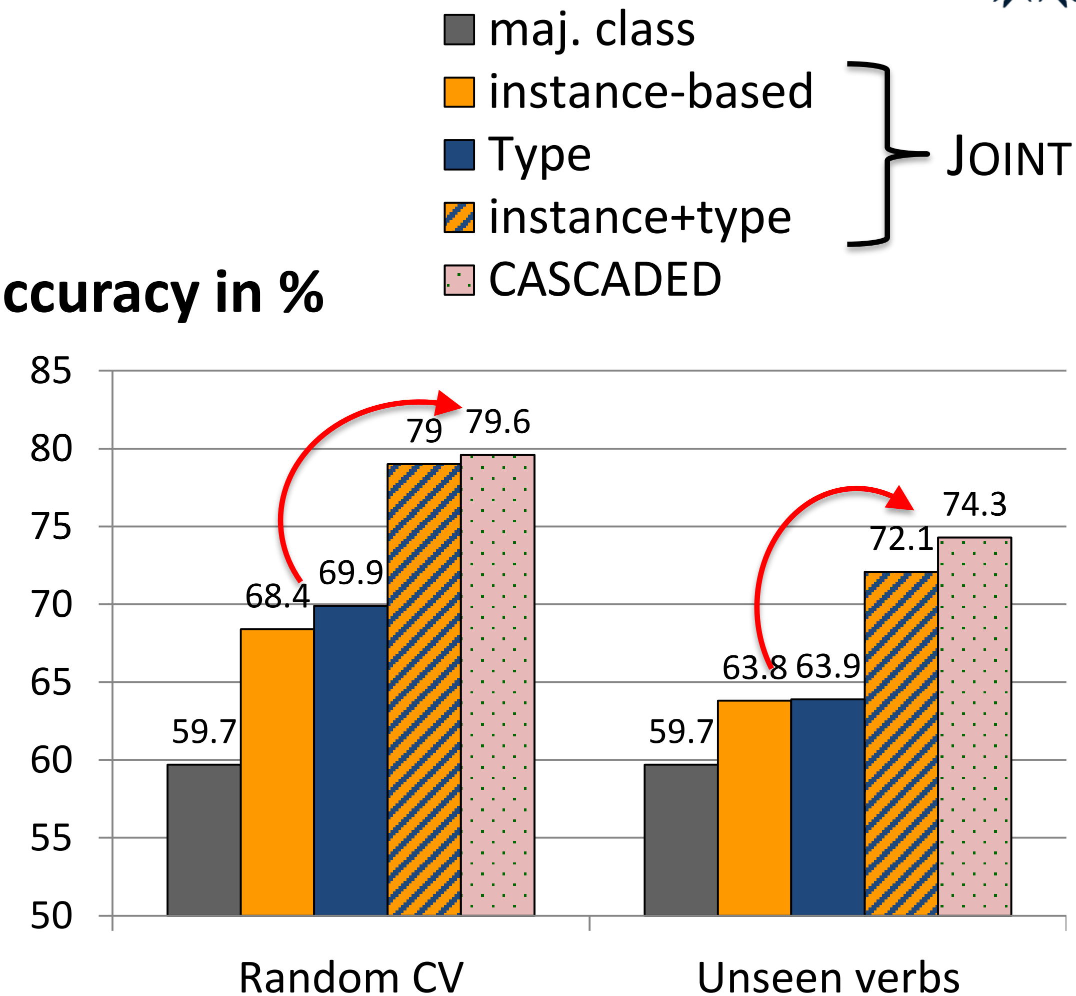
102 texts, 10355 clauses
3 annotators, κ=0.61

60% **static**
20% **episodic**
20% **habitual**

F1-scores



Cascaded model improves identification of habituals in free text.



Both instance- and type-based features are needed!

Computational modeling of situation entity types

[ACL 2015, LAW 2015]

is the main referent generic?

[ACL 2014]

lexical aspectual class

[EMNLP 2014]

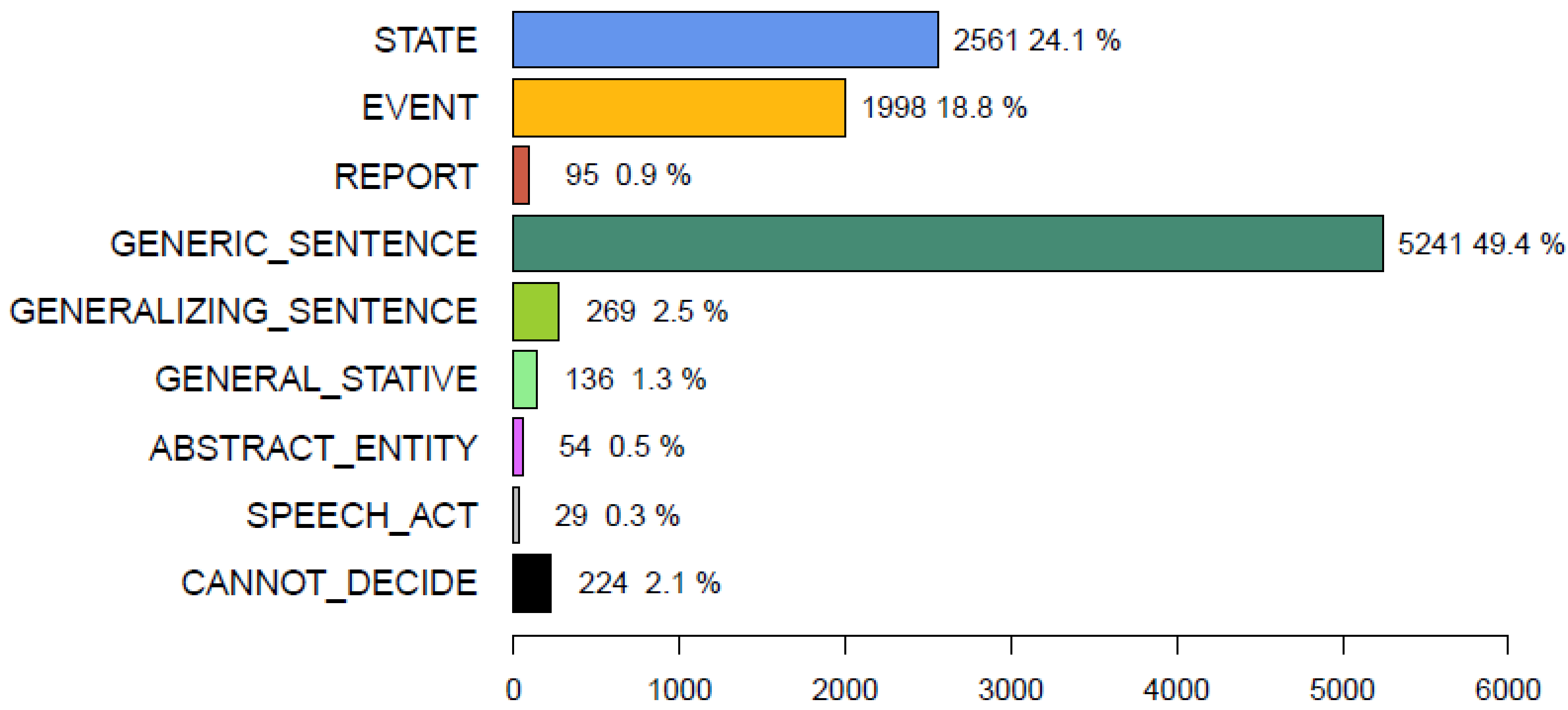
recognize habituality

entire documents, segmented into clauses

automatic classification of situation entity types

[ongoing work]

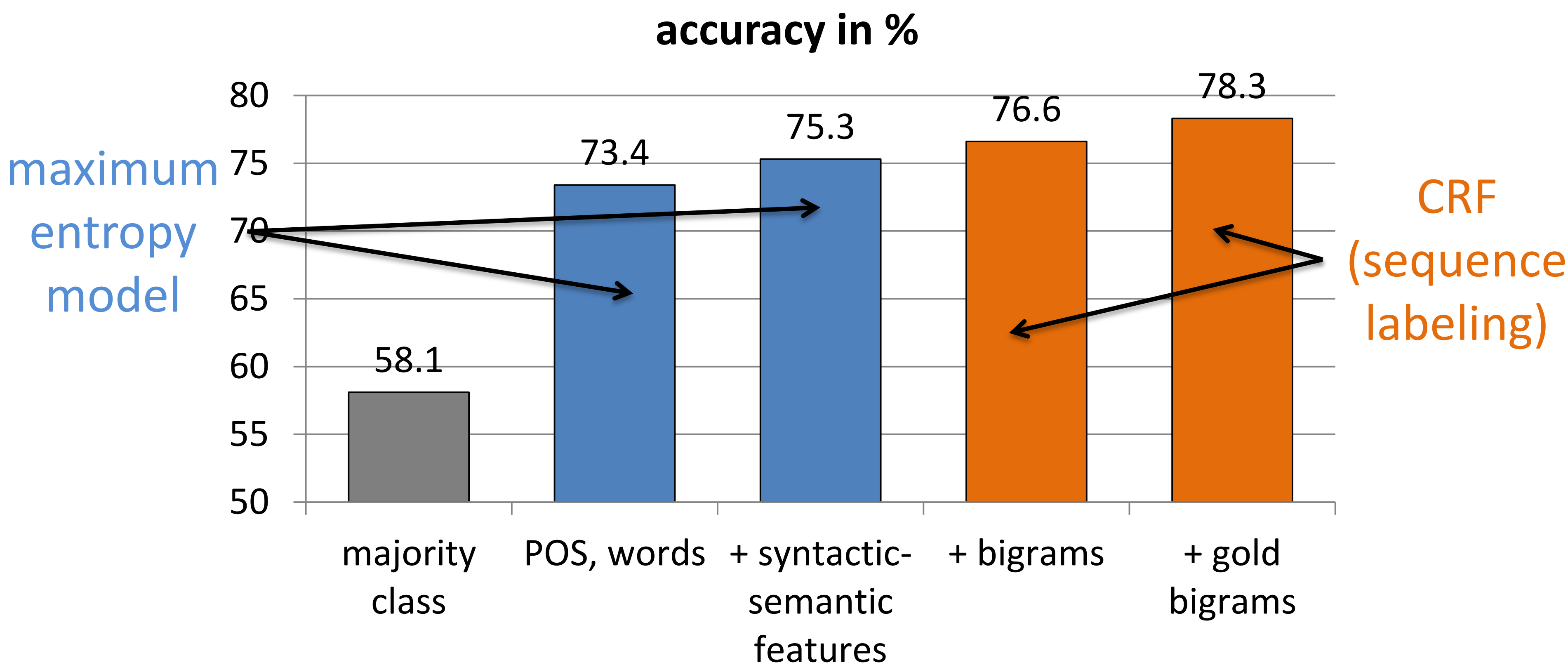
Situation entity type distribution in Wikipedia data



Situation entity types (intermediate results)

development set, ~8000 clauses

STATE, EVENT, GENERIC SENTENCE, GENERALIZING SENTENCE
(other situation entity types infrequent in Wikipedia data)



Situation entity types (intermediate results)

	STATE	EVENT	GENERIC SENTENCE CE	GENERALIZING NG SENTENCE SENTENCE
STATE	1216	190	591	11
EVENT	133	1372	14	153
GENERIC SENTENCE	484	121	3548	23
GENERALIZING G SENTENCE	30	43	97	44

- GENERALIZING SENTENCE: not enough data?
- confusion between GENERIC SENTENCE and STATE (was also observed in manual annotation)

On-going / future work

- identification of ABSTRACT ENTITIES (FACTS and PROPOSITIONS)
- identification of SPEECH ACTS (IMPERATIVES and QUESTIONS)
- investigate interaction of prediction of **features** (main referent, clausal aspect) and **situation entity types**
- investigate impact of different **genres / domains** (using MASC)
- create models for labeling situation entity types and **discourse modes**
- integrate situation entity type information in computational models of discourse, e.g., identification of **coherence relations** or **temporal processing**

Summary

- Groundwork for computational models of a novel approach to discourse analysis: complementary to existing approaches such as RST, Penn / Prague DTB, SDRT.
- Computational modeling of various aspectual distinctions (habituality, lexical aspectual class): useful for text understanding tasks such as temporal processing
- Recognition of genericity: knowledge acqusition from text

different types of clauses contribute differently to structure of discourse

Thank you!

http://www.coli.uni-saarland.de/projects/sitent

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