

Automatic identification of generic expressions

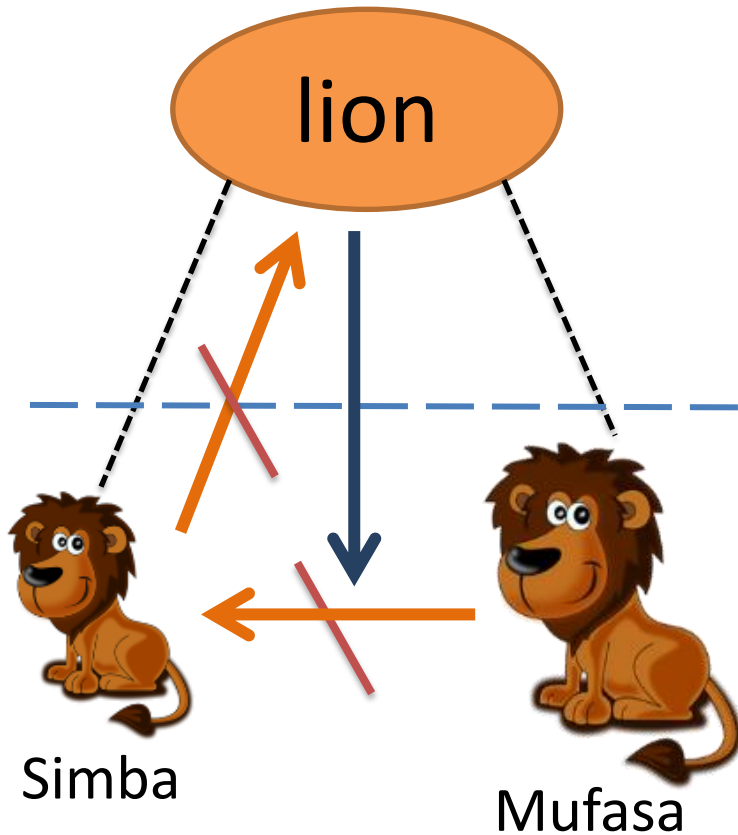
Annemarie Friedrich
afried@coli.uni-saarland.de

joint work with

Alexis Palmer, Melissa Peate Sørensen and Manfred Pinkal

Computational Linguistics, Universität des Saarlandes

Generic vs. non-generic expressions



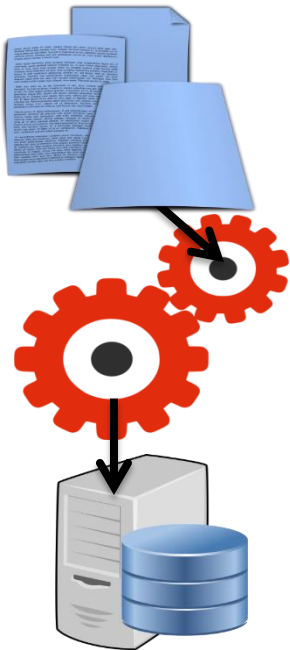
different
entailment properties

Lions are dangerous.

Mufasa is dangerous.

Simba is dangerous.

Identifying generic expressions: why?



knowledge
extraction
from text



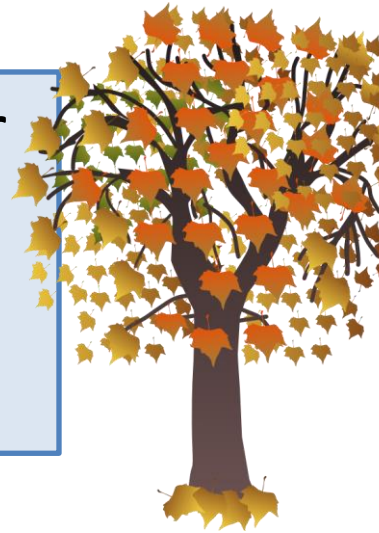
natural language
understanding

How? Discourse context matters

Previous work (Reiter & Frank 2010):

classification of noun phrases (in isolated sentences)

- a) Sugar maples also have a tendency to color unevenly in fall. (*generic*)
- b) The recent year's growth twigs are green and turn dark brown. (*generic*)

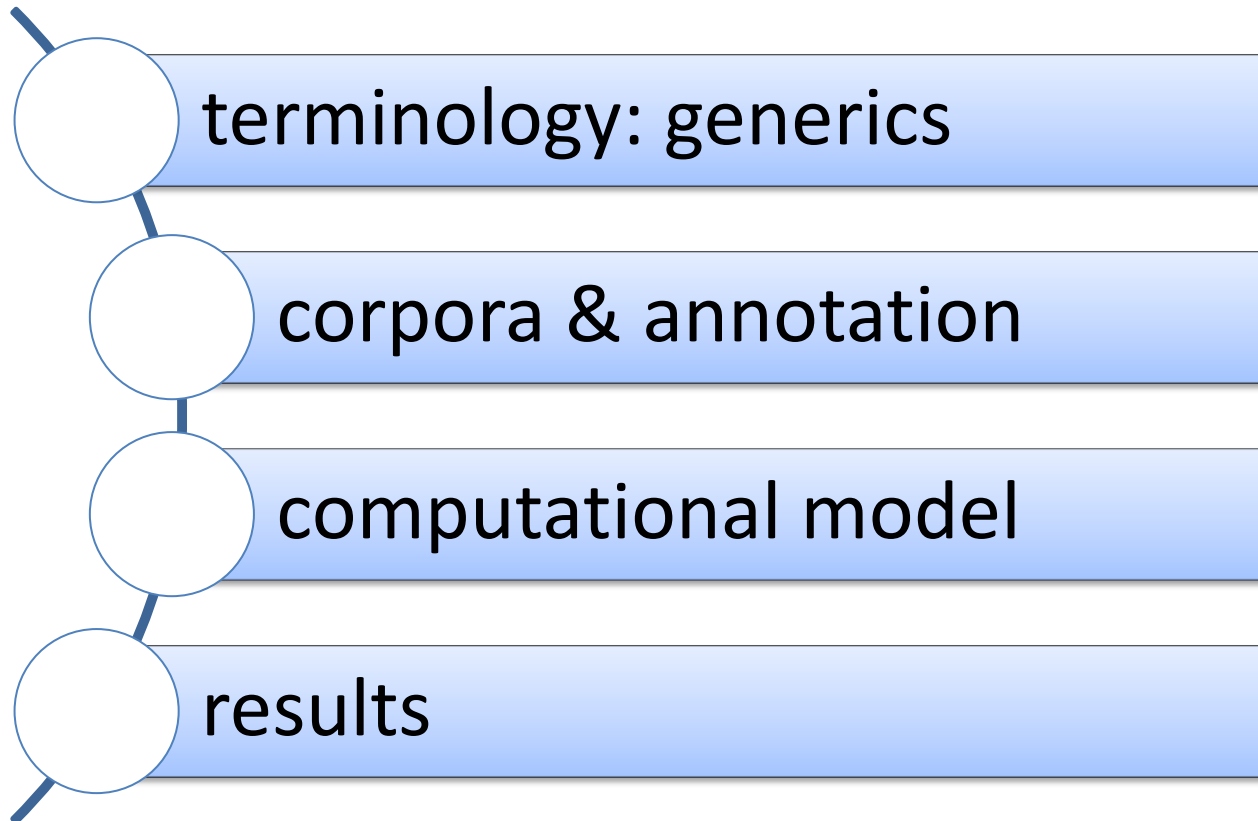


Discourse-sensitive approach (Friedrich & Pinkal 2015):

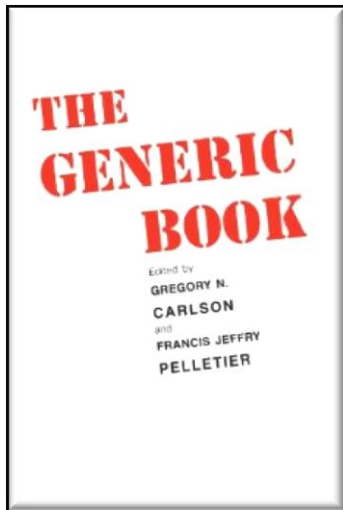
sequence labeling task

classification of (subject) noun phrases & clauses

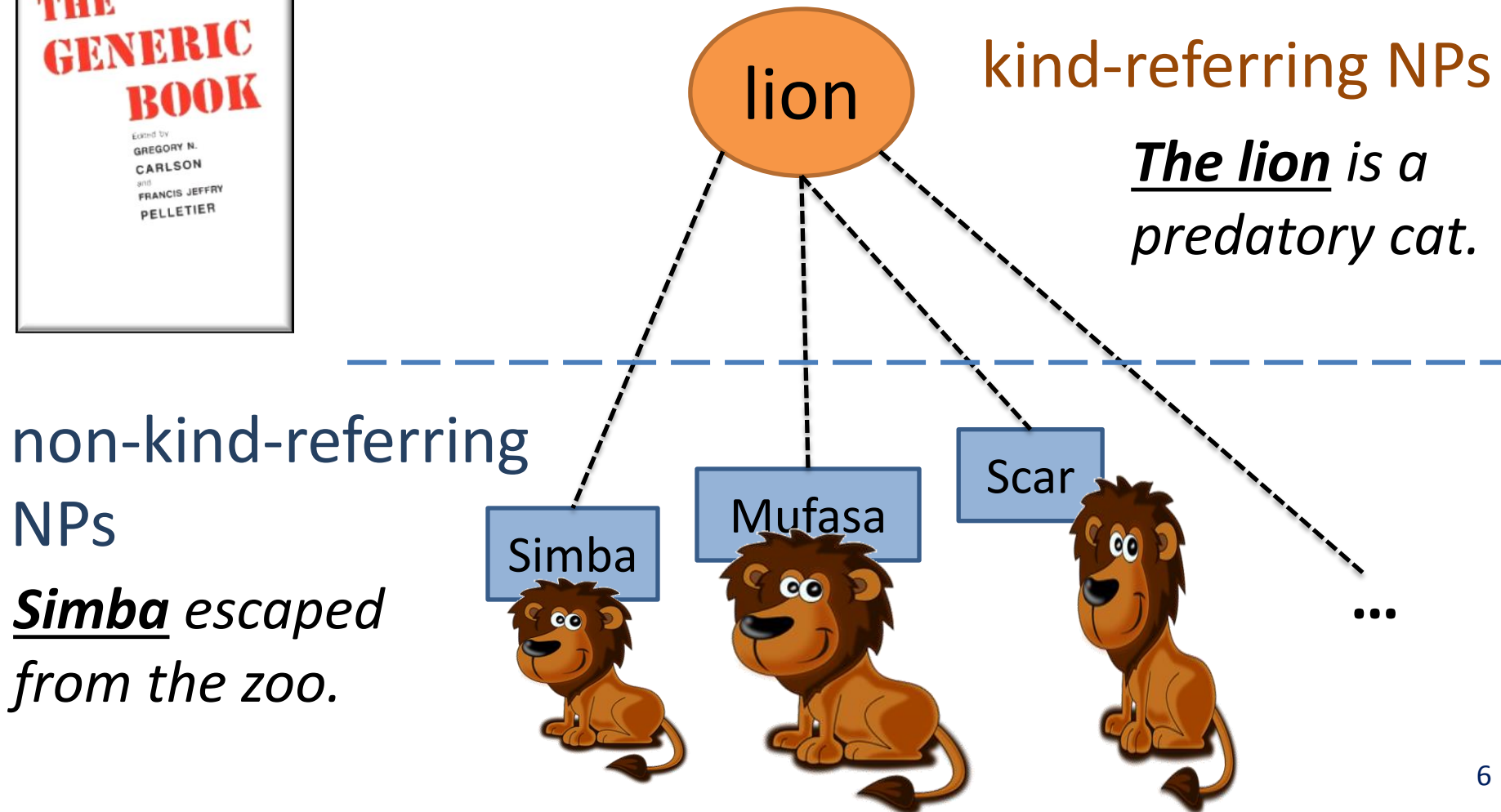
Overview of talk



Terminology: reference to kinds



Krifka et al. (1995): Genericity: An Introduction.



NP-level: reference to kinds

form of NP not sufficient

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

clause / context matters

Terminology: clause-level genericity

characterizing sentences

generalizations over situations



	lexically characterizing sentences	habitual sentences
kind-referring subject	<i>Lions have manes.</i>	<i>Lions eat meat.</i>
non-kind-referring subject	<i>John is tall.</i>	<i>John drives to work.</i>

Terminology: clause-level genericity

characterizing sentences

generalizations over situations



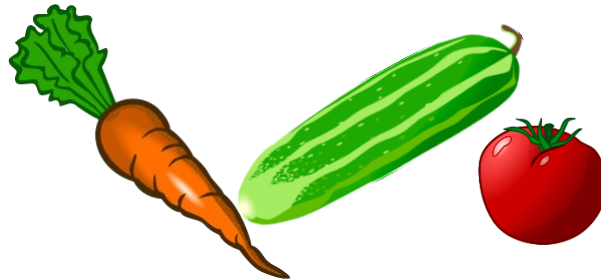
	lexically characterizing sentences	habitual sentences
kind-referring subject	<i>Lions have manes.</i>	<i>Lions eat meat.</i>
non-kind-referring subject	<i>John is tall.</i>	<i>John drives to work.</i>

Generic sentences

- The term is used for various (NP- and clause-level) phenomena.
- Generic sentences are not rendered false by the existence of counter-examples.

Lions eat meat.

The lion in our zoo is weird, though, it only eats vegetables.



Related Work

- **ACE corpora**
 - Automatic Content Extraction (2002-2008)
 - largest corpora annotated with NP-level genericity to date, ~40k NPs
- Reiter & Frank (ACL 2010):
 - **“Identification of generic noun phrases”**
 - use a variety of NP-based and clause-based features
 - Bayesian network (Weka)

ACE entity class annotations

ACE-2:

generic = “any member of the set in question”

specific = “some particular, identifiable member of that set”

ACE-2005:

GEN = kind-referring

SPC = non-kind-referring

NEG = negatively quantified NPs

There are no confirmed suspects yet.

USP = underspecified: ambiguous cases

There are new opportunities for women in New Delhi.

and mentions of entities “whose identity would be difficult to locate”: *Officials reported ...*

ACE-2005: agreement study



annotations available from LDC
agreement study:

exactly-matching entity mention spans (~90%)

533 documents

adjudication

final corpus

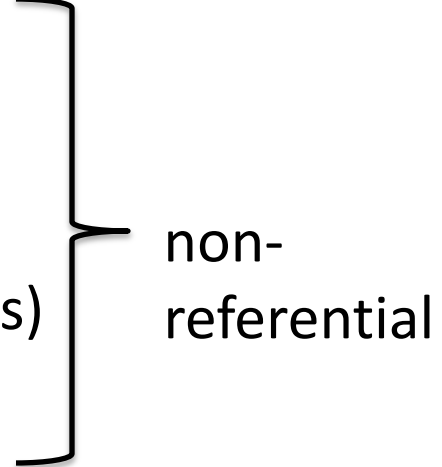
news, broadcast news,
broadcast conversation,
forum and weblog texts

		annotator 2			
		SPC	USP	GEN	NEG
annotator 1	SPC	28168	1575	684	3
	USP	1142	1954	963	2
	GEN	757	1261	1707	10
	NEG	8	5	7	71

Cohen's $\kappa = 0.53$

confusion of SPC/GEN with USP is high

Problems of the ACE annotation guidelines

- **predicative uses** are marked
 - *John is a nice person. (specific)*
 - *John seems to be a nice person. (generic)*
 - **noun modifiers** in compounds (9.5% of all mentions) are marked as generic: subway system
- 
- non-referential
- guidelines mix **genericity** and **specificity**
 - (specificity = speaker has a particular referent in mind)
 - Officials reported...
 - this is not underspecified: it is not generic, but nonspecific

WikiGenerics corpus

102 Wikipedia texts

about animals, sports, politics, science, biographies, ...
10279 clauses, aim: balanced corpus (many generics)

Annotation scheme

motivated by **semantic theory** (Krifka et al. 1995)

study references to and statement about kinds

(Task NP, Task Cl, Task Cl+NP)

(other aspects of genericity → future work)

contribution of clauses to **discourse**:

characterizing statements ≠ particular events or states

→ relevant for processing temporal structure of discourse

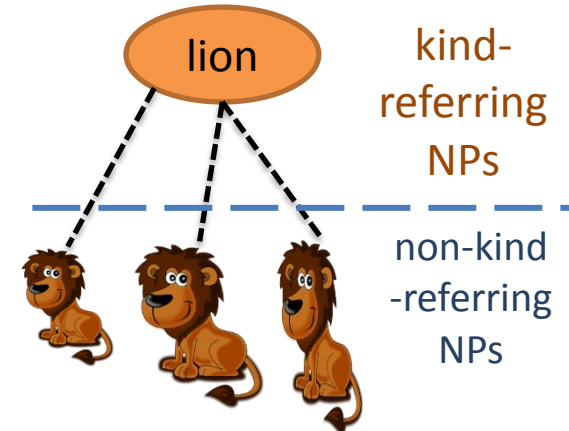
Task NP: genericity of subject

generic: references to kind / class

The lion is a predatory cat.

Lions have manes.

A lion may eat up to 30kg in one sitting.



non-generic: references particular individual(s)

Simba flees into exile.

A lion must have eaten the rabbit. (nonspecific)

Lions are in this cage.

Task C1: genericity of clause

generic: characterizing statements about kinds
subject must be **generic**.

The lion is a predatory cat.

Lions eat up to 30kg in one sitting. (habitual)

non-generic: statements about particular
individuals or particular events.

John is a nice guy.

John cycles to work. (habitual)

Task Cl+NP: clause and subject

clause subject	generic	non-generic
generic	<i><u>Lions</u> have manes. <u>Lions</u> eat meat.</i>	<i><u>The blobfish</u> was voted the “World’s Ugliest Animal”. <u>Dinosaurs</u> died out.</i>
non-generic	-- --	<i>John is a nice guy. John cycles to work.</i>

habitual vs. other types of clauses: future work!

Annotation process

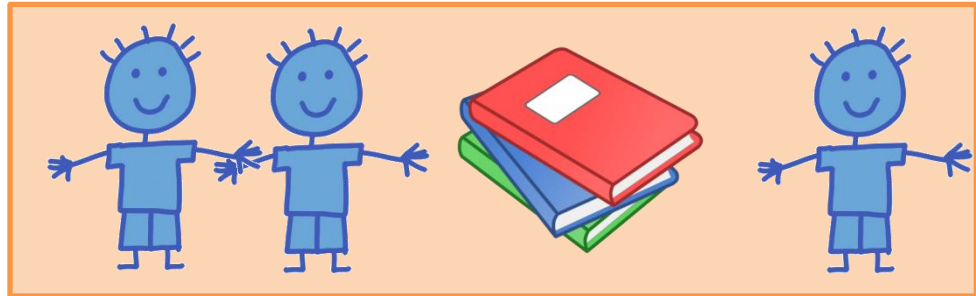


SPADE system

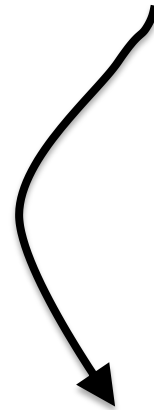


segmentation into clauses

subjects are not pre-marked
1) Lions are big cats
2) and eat meat.



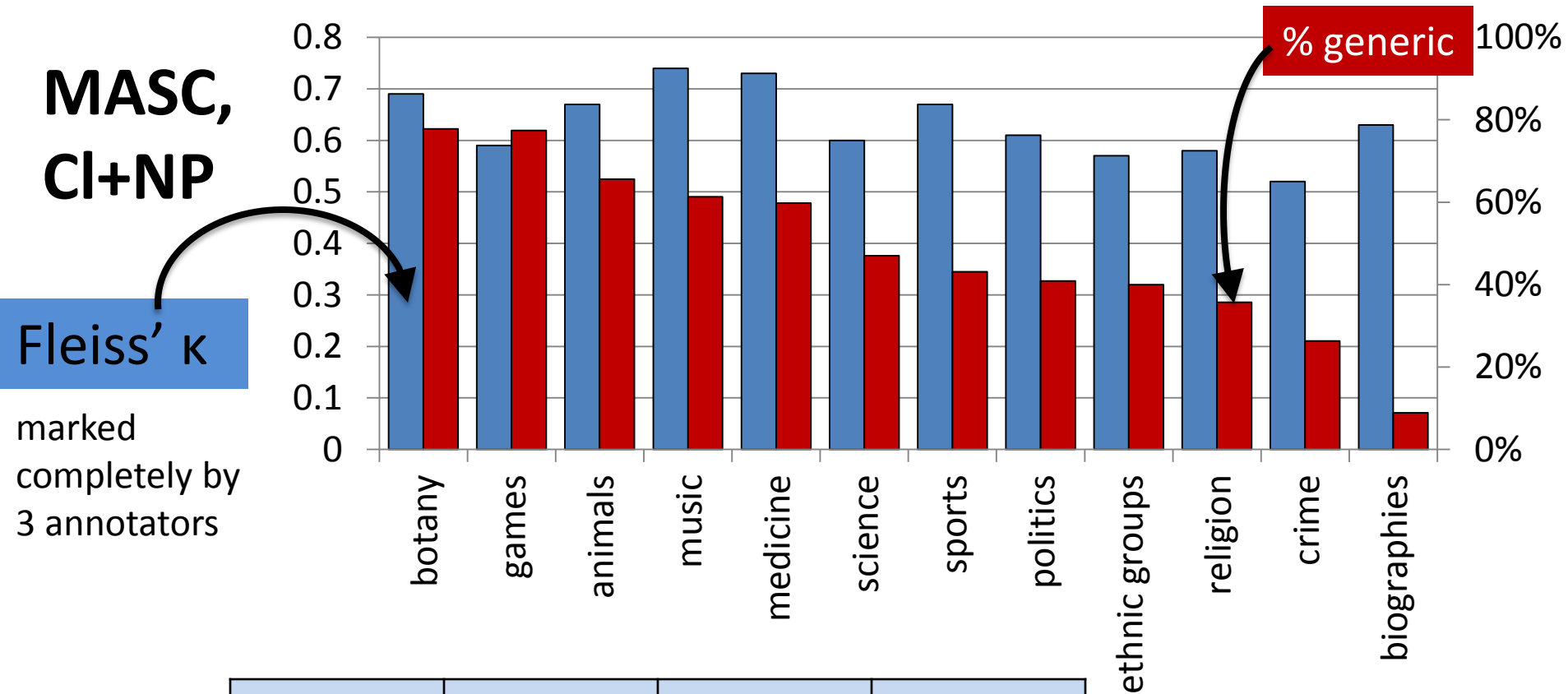
3 annotators label all texts



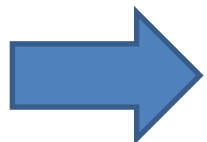
majority vote



Inter-annotator agreement: WikiGenerics



Task NP	Task CL	Task CI+NP	% generic
0.69	0.72	0.68	50.1%



balanced corpus, substantial agreement



Computational model

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
...
currentLabel=GEN and previousLabel=GEN : 1
...

*features:
indicator functions*

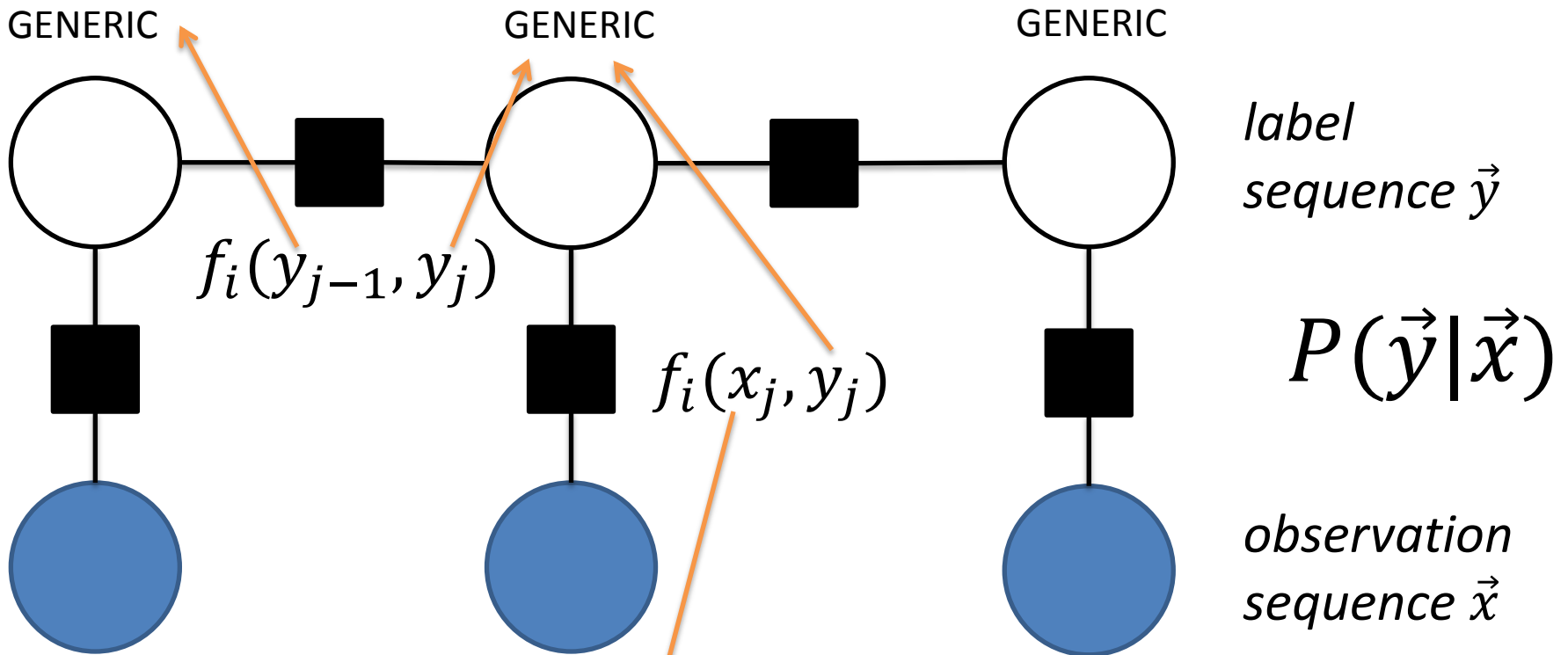


GENERIC

GENERIC

sequence of labels

Linear-chain Conditional Random Field



Acer saccharum is a deciduous tree.

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

The recent year's growth twigs are green.



Linear-chain Conditional Random Field

Probability of label sequence \vec{y} given observation sequence \vec{x}

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

sum over observations in \vec{x}

sum over feature functions

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

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

Discriminative training (maximum likelihood, CRF++ toolkit uses L-BGFS)₂₃

Features [see Reiter & Frank 2010]

extracted from dependency
parses (Stanford parser)

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,...

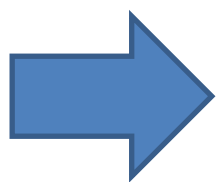
Clause-based features	
dependency relations	between (subject) head and governor etc.
tense	past, present, future
progressive	true, false
perfective	true, false
voice	active, passive
part-of-speech	POS of head
temporal modifier	true, false
number of modifiers	numeric
predicate	lemma of head
adjunct-degree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

Results on ACE data: NP-level

ACE-2: SPC, GEN		
System	F1	Acc.
majority class	46.5	86.8
Bayes Net (R&F)	69.8	80.4
CRF (unigram)	71.3	88.5*
CRF (bigram)	72.4	88.9*
<i>CRF (bigram, gold)</i>	<i>76.0</i>	<i>90.1</i>

* difference statistically significant

ACE-2005 (subject mentions) SPC, GEN, USP		
System	F1	Acc.
majority class	28.6	75.1
Bayes Net (R&F)	52.7	72.5
CRF (unigram)	53.6	77.7*
CRF (bigram)	53.7	77.8
<i>CRF (bigram, gold)</i>	<i>58.6</i>	<i>79.6*</i>



Our model outperforms previous work.

Gold information → discourse helps.

Few generic instances, problems in annotation guidelines.

WikiGenerics Task NP: genericity of subject

The lion is a predatory cat.

(generic)

Simba had to flee.

(non-generic)

System	Macro-avg. F1	Accuracy
majority class	35.9	56.1
Bayes Net (R&F)	72.3	71.7
CRF (unigram)	75.9	76.4
CRF (bigram)	78.8	79.1
CRF (bigram, gold)	82.7	83.0

discourse information



WikiGenerics Task Cl: genericity of clause

The lion is a predatory cat.

(generic)

Simba had to flee.

(non-generic)

System	Macro-avg. F1	Accuracy
majority class	35.1	43.7
Bayes Net (R&F)	73.7	73.5
CRF (unigram)	77.4	77.4
CRF (bigram)	80.7	80.7
<i>CRF (bigram, gold)</i>	82.8	82.8

discourse
information



WikiGenerics Task Cl+NP: three-way task

The lion is a predatory cat.

Simba had to flee.

The blobfish was voted the most ugly animal of the world.

(CLAUSE_subject)

(GEN_gen)

(NON-GEN_non-gen)

(NON-GEN_gen)

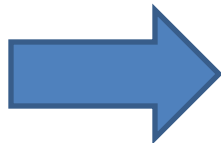
System	Macro-avg. F1	Accuracy
majority class	22.4	50.4
Bayes Net (R&F)	56.4	65.2
CRF (unigram)	63.4	74.0
CRF (bigram)	65.8	77.4
<i>CRF (bigram, gold)</i>	69.0	80.6

discourse
information



Feature set ablation

System	Accuracy		
	Task NP	Task Cl	Task Cl+NP
CRF (bigram)	79.1	80.7	77.4
- clause features only	76.0	78.8	74.3
- NP features only	74.1	71.7	70.0

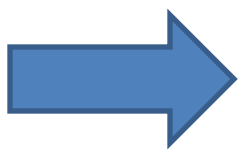
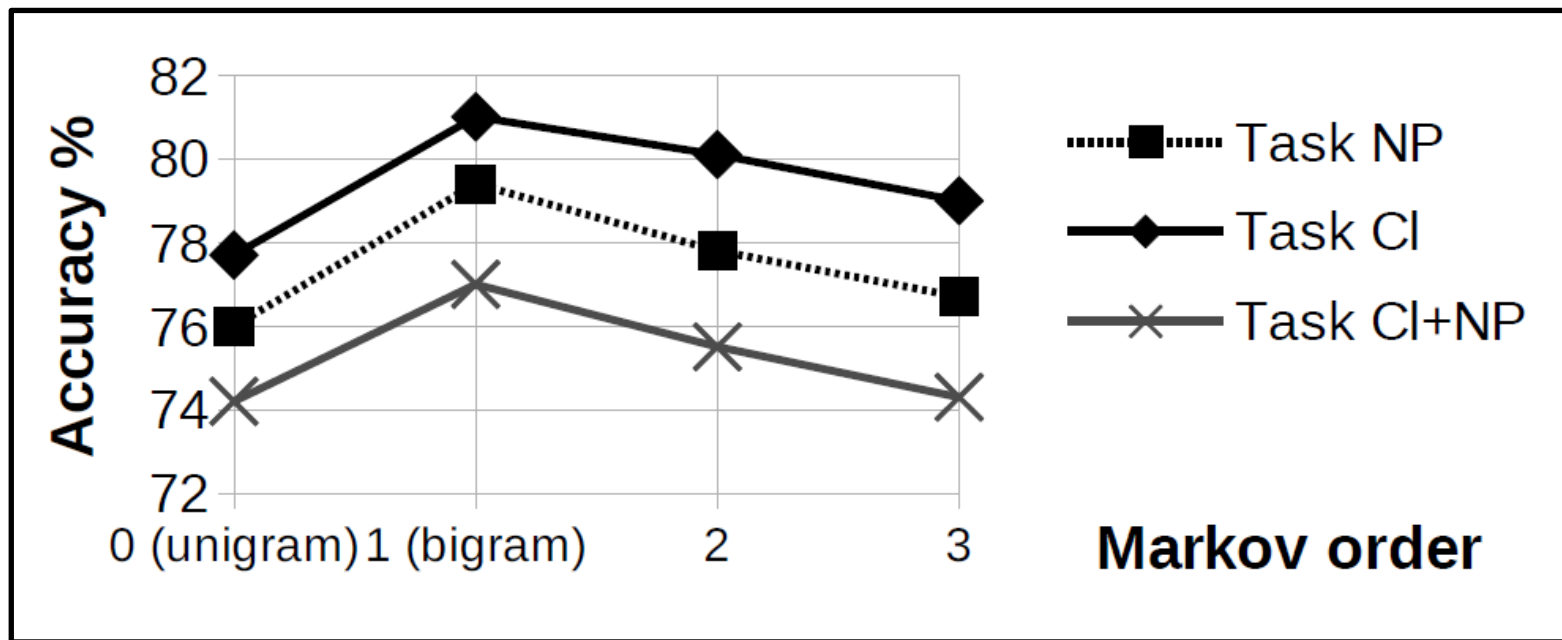


It strongly depends on clause whether an NP is interpreted as generic or not.

Markov order

Mallet toolkit

What happens if we take more than the immediately preceding label into account?



- using only the preceding label is optimal
- labels of non-adjacent clauses **do** influence each (score is optimized for entire sequence)

Conclusions

We classify NPs and clauses with regard to their genericity.

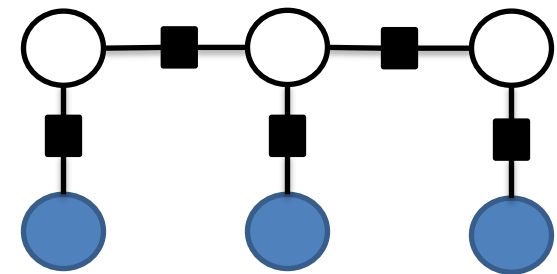


WikiGenerics corpus
balanced
substantial agreement

CRF finds **optimal label sequence**
for clauses of a document,
combining information from clause
and surrounding labels



discourse information matters!



Future work

- Genericity of NPs other than the subject
 - annotation + automatic classification
 - *Cats chase mice.*
- Related linguistic phenomena
 - habitual vs. episodic sentences
 - *John cycled to work today.*
 - *John cycles to work.*
- Integration into applications



Thank you



Alexis Palmer



Melissa Peate Sørensen



Manfred Pinkal

Questions?

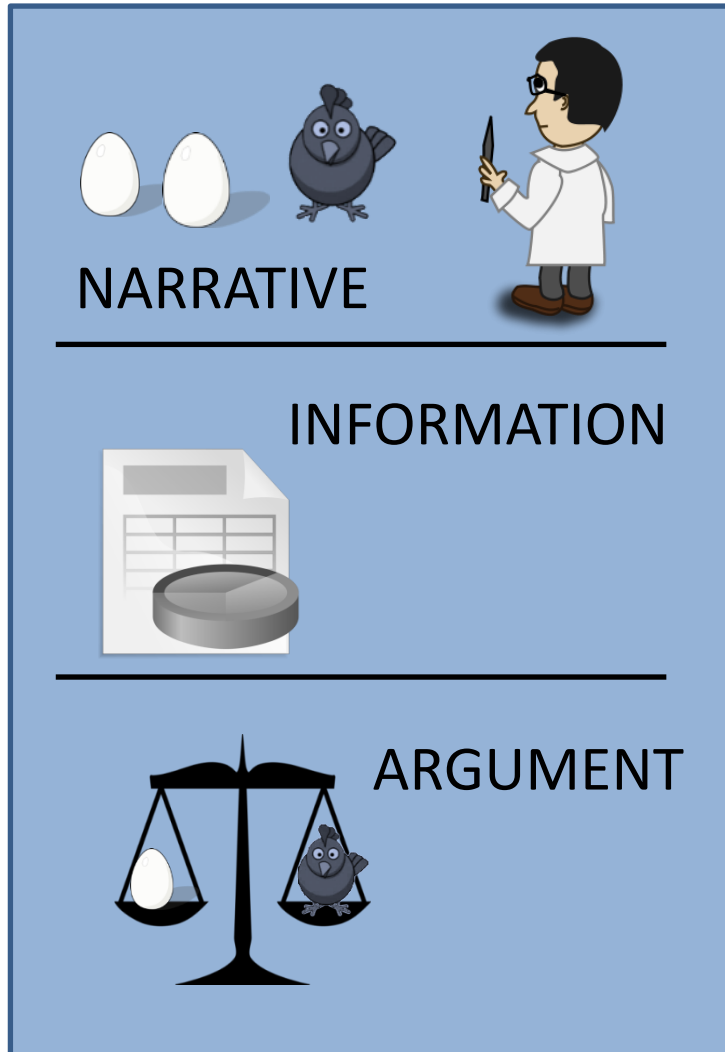
www.coli.uni-saarland.de/projects/sitent

The bigger picture

**Annotation and automatic
classification of situation entity types**

Discourse modes [Smith 2003]

Modes of discourse [Smith 2003]



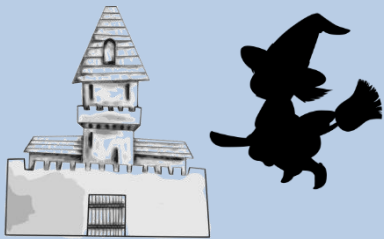
Different passages of a text can have different discourse modes.

one text \approx one genre

one text \neq one discourse mode

Modes of discourse [Smith 2003]

NARRATIVE



temporal
progression

REPORT



temporal
progression

DESCRIPTION



temporal /
spatial
progression

INFORMATION



metaphorical
progression

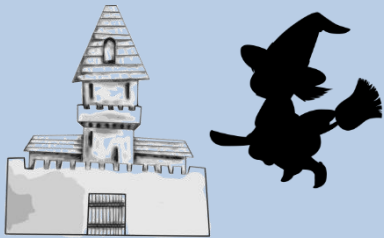
ARGUMENT



metaphorical
progression

Modes of discourse [Smith 2003]: Situation entity types

NARRATIVE



EVENT,
STATE

REPORT



EVENT, STATE,
general statives

DESCRIPTION



EVENT, STATE,
ongoing EVENT

INFORMATION



general
statives

ARGUMENT



FACT,
PROPOSITION,
general statives

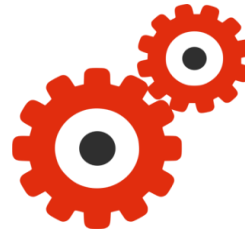
Situation entity types

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

Motivation



Annotation of
large data set
(MASC)

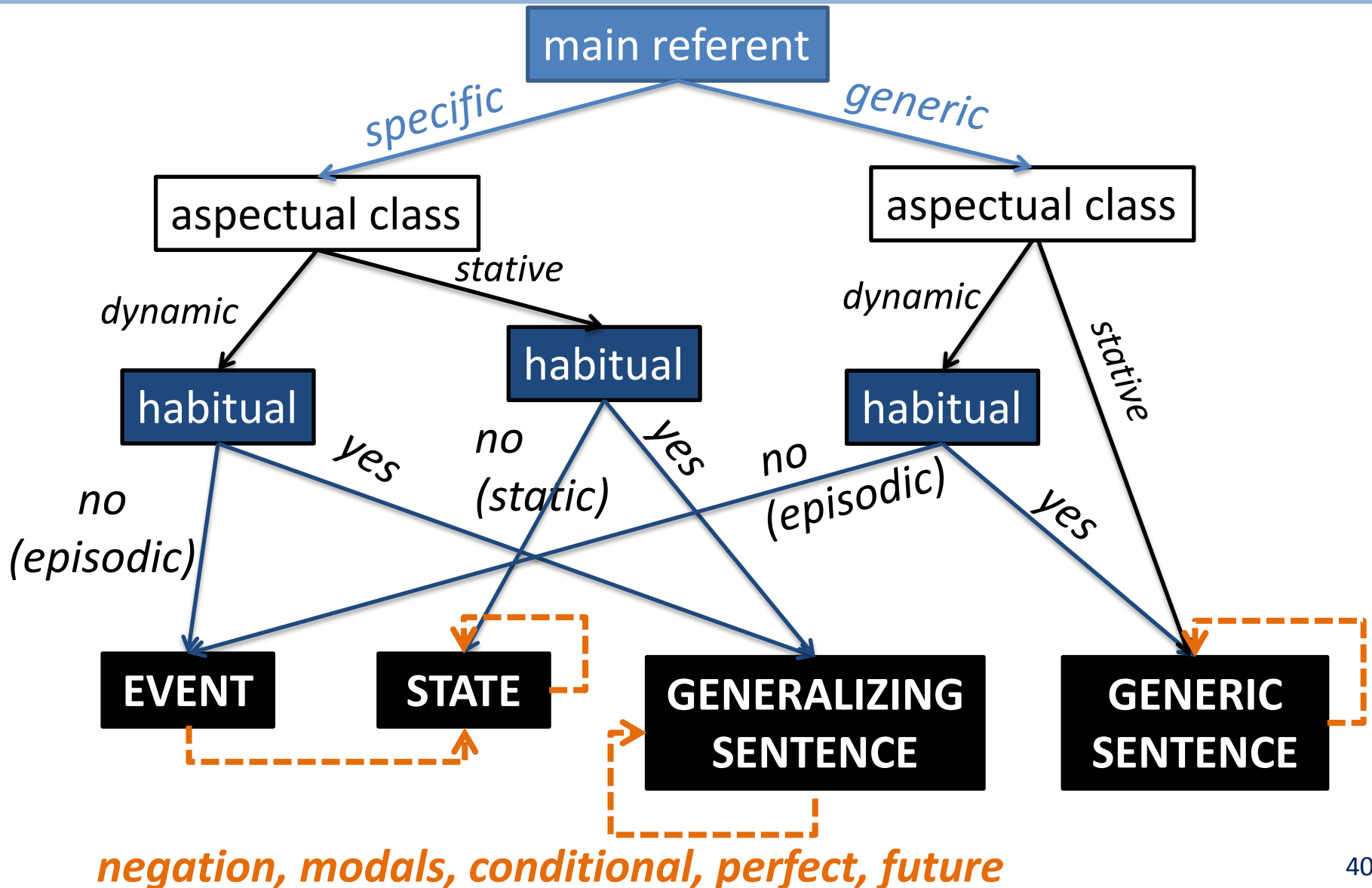


computational
modeling

assess the applicability of SE type
classification as described by Smith [2003]
borderline cases? human agreement?

training, development, evaluation of automatic
systems for classifying SEs and related tasks:
improve temporal discourse processing

Features & SE types



Feature: fundamental aspectual class

[Friedrich & Palmer, ACL 2014]



Juice **fills** the glass.
STATIVE

The glass **was filled** with juice.
BOTH readings possible



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

Summary

- **generics**: distinguish GENERIC SENTENCES from other situation entity types
[Friedrich & Pinkal 2015]
- **lexical aspectual class**: distinguish STATES and EVENTS [Friedrich & Palmer 2014]
- **habituals**: work in progress
- **full classification task**: work in progress

References

ACE corpora: <https://www ldc.upenn.edu/collaborations/past-projects/ace>

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