



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

CIS Talks LMU München, December 2016

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joint work with Alexis Palmer (now University of North Texas)
and Manfred Pinkal (Saarland University)

Thanks!



Alexis Palmer



Manfred Pinkal



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Sorensen



Liesa Heuschkel



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Bocionek



Fernando
Ardente



Ruth Kühn



Ambika Kirkland



Damyana Gateva

Discourse modes [Smith, 2003]



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...

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. ...

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.

Discourse modes

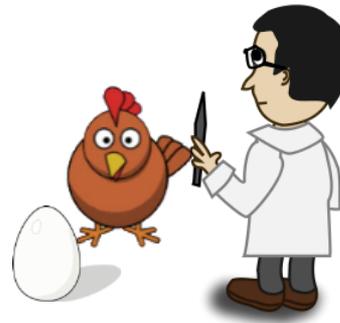


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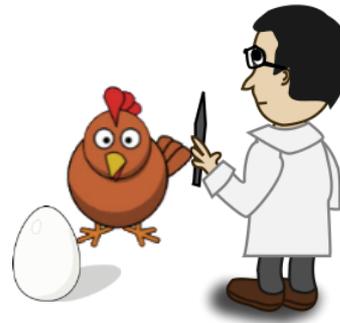
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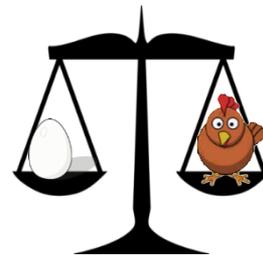
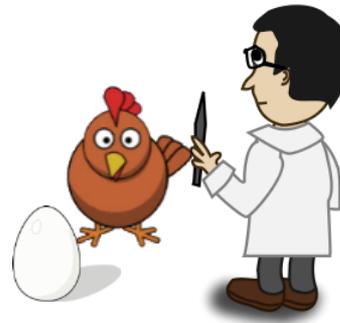
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ARGUMENT COMMENTARY



Discourse modes



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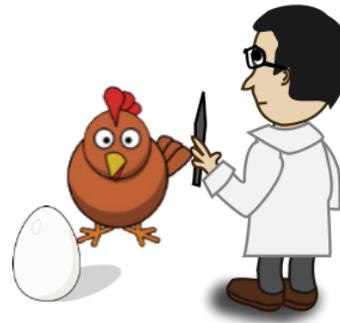
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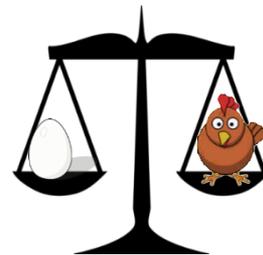
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**ARGUMENT
COMMENTARY**



one text
≈ one genre

one passage
≈ one discourse
mode



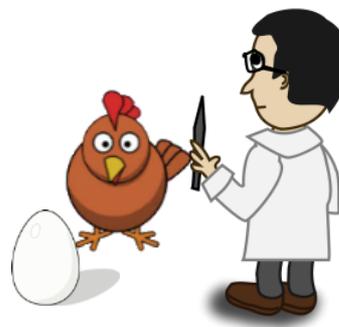
Discourse modes & situation entity types



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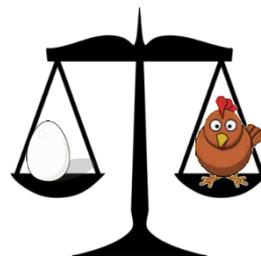
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NARRATIVE



INFORMATION



**ARGUMENT
COMMENTARY**

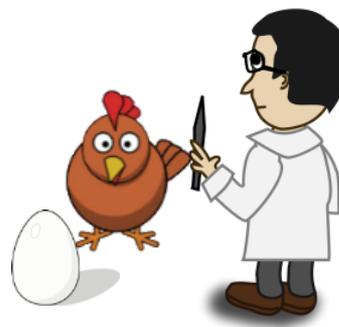
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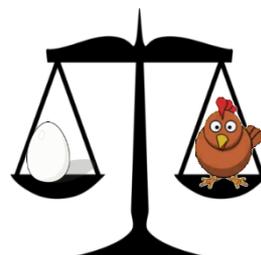


NARRATIVE

STATE
EVENT



INFORMATION



ARGUMENT
COMMENTARY

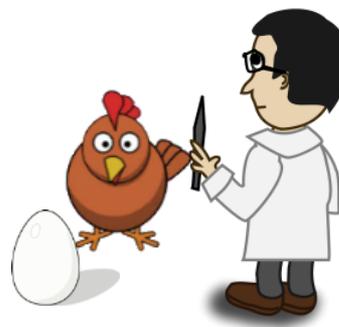
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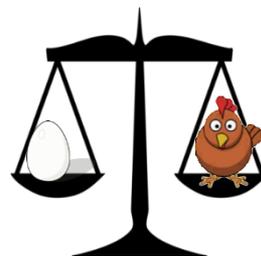
NARRATIVE

STATE
EVENT



INFORMATION

GENERIC SENTENCE
GENERALIZING SENTENCE



ARGUMENT
COMMENTARY

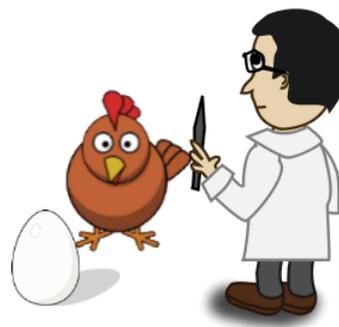
Discourse modes & situation entity types



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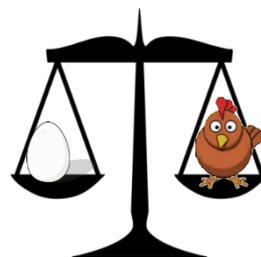
NARRATIVE

STATE
EVENT



INFORMATION

GENERIC SENTENCE
GENERALIZING SENTENCE



ARGUMENT
COMMENTARY

STATE, EVENT, ABSTRACT
ENTITIES, GENERIC /
GENERALIZING SENTENCES



Situation entity types

- Inventory of **aspectual clause types** motivated by a theory of discourse [Smith 2003]



What is clause-level aspect?

- **aktionsart**

[Vendler 1957, Bach 1986]

state	The ship is in motion.
event	The ship moved.
process	The ship is moving.

- **habituals / genericity** [Krifka et al. 1995]

John cycles to work.
Students like coffee.

Why model these phenomena?

- understand temporal relations in discourse
- distinguish between / extract different types of knowledge
- identify different modes of discourse

Situation entity types: summary



coercion to STATE: negation, modality, future, perfect, conditionality, subjectivity		Julie likes Cooper.
		Julie likes did not kill the mouse.
		Julie met Cooper two years ago.
		..., said the zookeeper.
	GENERIC SENTENCE	Owls are nocturnal animals.
	GENERALIZING SENTENCE	Julie likes often teases Cooper.
	IMPERATIVE	Julie, tease Cooper!
	QUESTION	Does Julie tease Cooper?

What are the major differences between these types?





Situation entity types: summary

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

lexical aspectual class

	Julie likes Cooper.
	Julie did not kill the mouse.
EVENT	Julie met Cooper two years ago.
- REPORT	..., said the zookeeper.
GENERIC SENTENCE	Owls are nocturnal animals.
	Julie often teases Cooper.
	Catch the mo... ?
	Why are the... on your slides?

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

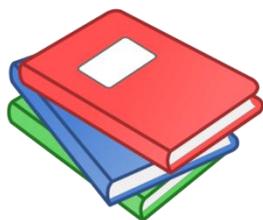
genericity

Does something happen repeatedly or once?

habituality



Data sets and annotation procedure



MASC

25,000 clauses

*essays, letters, fiction,
technical, travel, news ...*

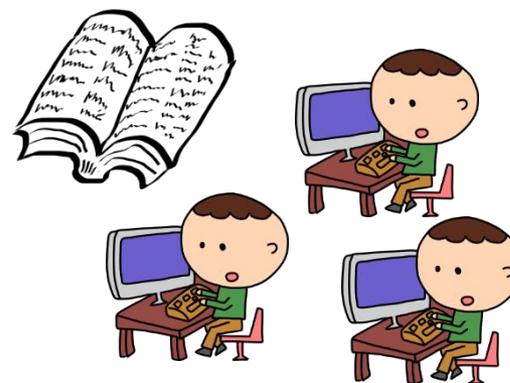


Wikipedia

10,000 clauses

*botany, animals, sports,
biographies, science, ...*

training phase
+ manual



segmentation into
clauses (SPADE)

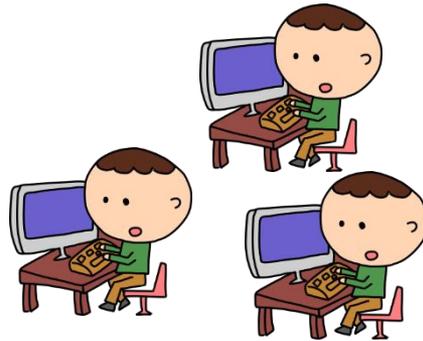
Annotators label

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

gold standard = majority vote
over labels of 3 annotators

(about 10% of automatically created
segments marked as “NO SITUATION”)

Inter-annotator agreement



Fleiss' κ

= how much agreement beyond chance was reached

Fleiss' κ : features		MASC / Wiki
aspectual class	stative, dynamic, both	0.69 / 0.64
main referent	generic, non-generic, cannot decide	0.69 / 0.65
habituality	episodic, static, habitual, cannot decide	0.55 / 0.67

Inter-annotator agreement



Situation entity type	% in gold standard		Fleiss' K
	MASC	Wikipedia	Krippendorff's diagnostics
STATE	49.8	24.3	0.67
EVENT	24.3	18.9	0.74
REPORT	4.8	0.9	0.80
GENERIC SENTENCE	7.3	49.7	0.68
GENERALIZING SENTENCE	3.8	2.5	0.43
QUESTION	3.3	0.1	0.91
IMPERATIVE	3.2	0.2	0.94
<i>undecided</i>	2.4	2.1	-



- **modeling of Vendler classes**
 - state, activity, accomplishment, achievement
 - Italian [Zarcone & Lenci 2008], German [Hermes et al. 2015]
 - stative vs. dynamic, completedness [Siegel & McKeown 2000]
- **modeling genericity**
 - identifying genericity of NPs / reference to kinds [Reiter & Frank 2010]
 - recognizing habituals [Mathew & Katz 2009]
- **labeling situation entities** [Palmer et al. 2007]
 - maximum entropy model, features: pos tags, words, linguistic
 - data set: 20 texts / 4391 clauses, Brown corpus, $\kappa=0.52$

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

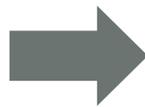
[EMNLP 2015]

is the main referent generic?

lexical aspectual class

recognize habituality

entire documents, segmented into clauses



automatic classification of situation entity types

[ACL 2016]

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

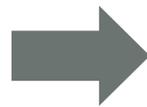
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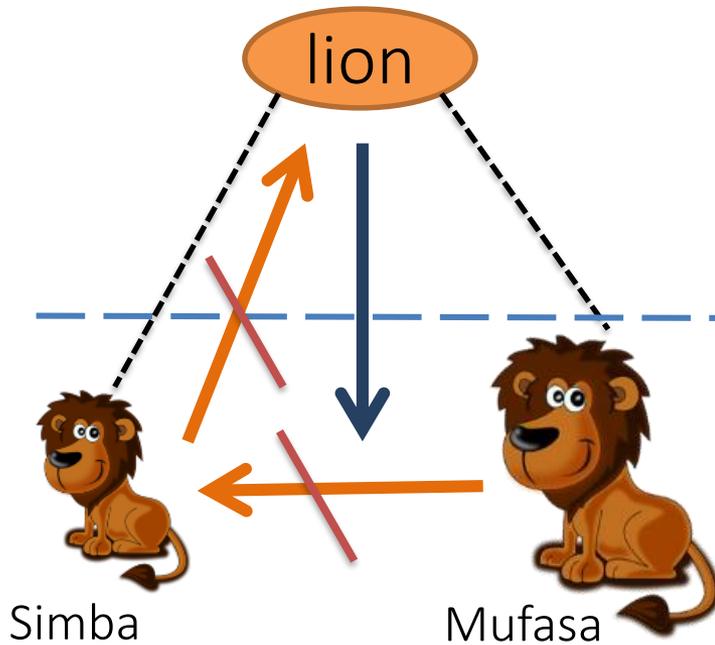
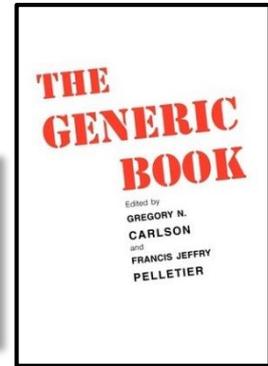
automatic classification of situation entity types

[ACL 2016]

Genericity



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



different
entailment properties

Lions are dangerous.

kind-referring
generic

Mufasa is dangerous.
Simba is dangerous.

non-generic



Reference to kinds

form of NP not sufficient

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

clause / context matters

Discourse-sensitive approach



WIKIPEDIA
The Free Encyclopedia

[The recent year's growth twigs]
are green and turn dark brown.

It's impossible to label
this without discourse
context!



Discourse-sensitive approach



WIKIPEDIA
The Free Encyclopedia

[Sugar maples **generic**] also have a tendency to color unevenly in fall.

[The recent year's growth twigs **generic**] are green and turn dark brown.



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



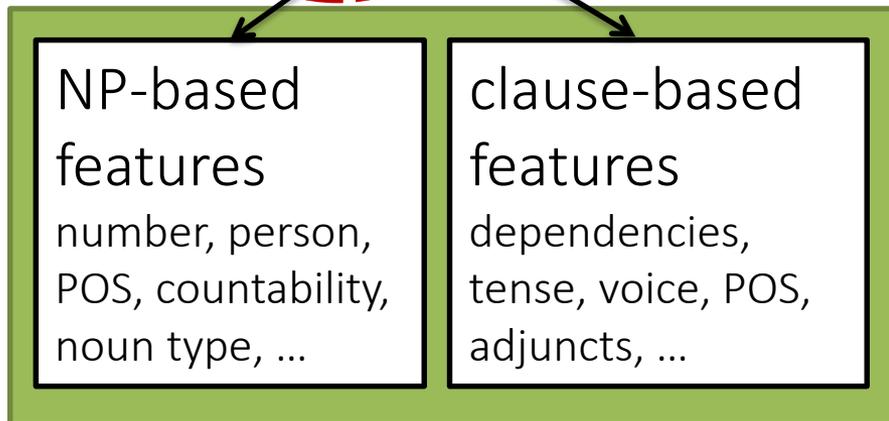
Baseline: identifying generic noun phrases

Data: ACE-2 & ACE-2005

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

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

Lions eat meat.



Bayesian network [Weka]

[Reiter & Frank ACL 2010]

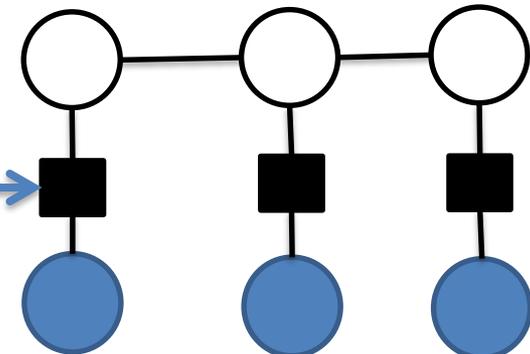
local decision for each NP

Linear Chain CRF

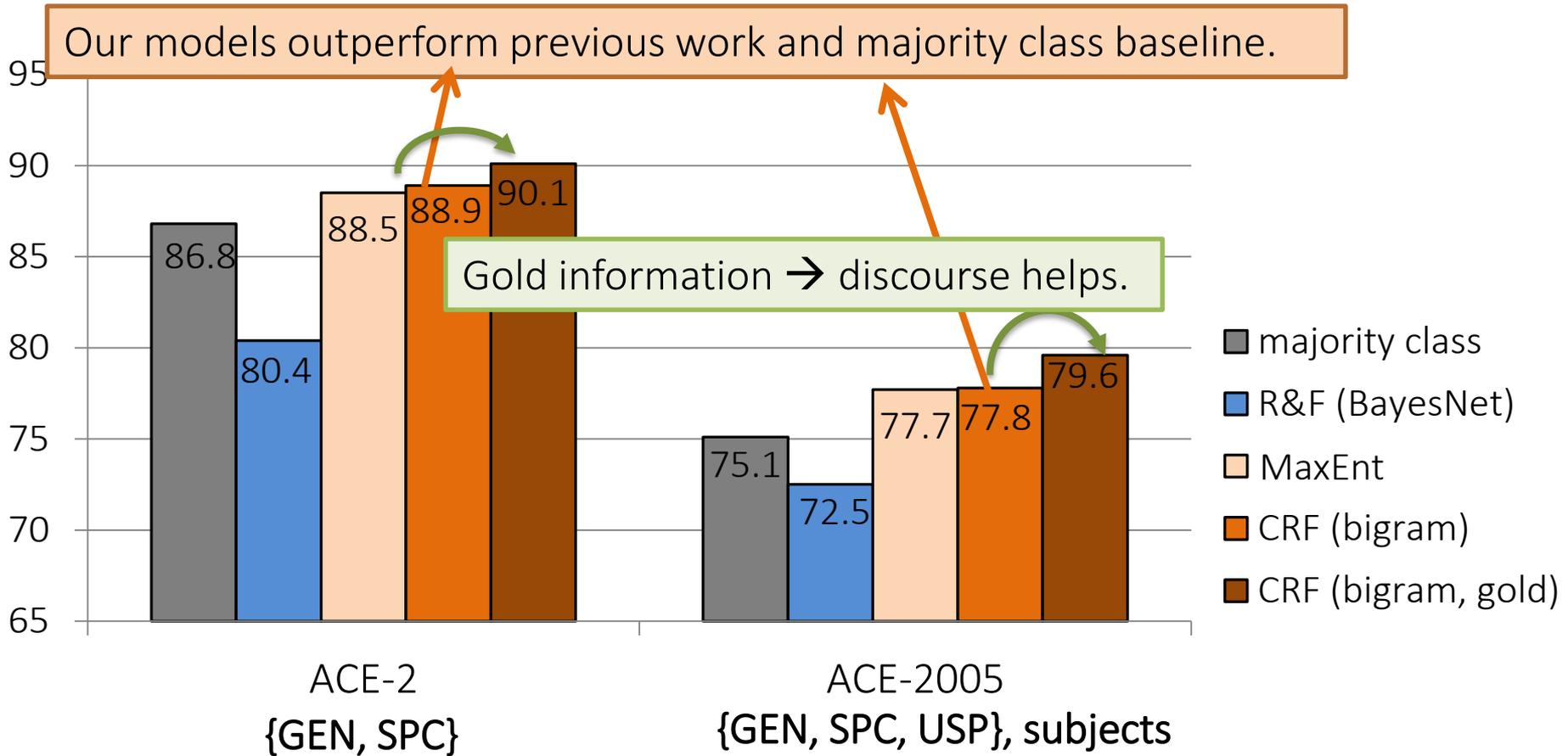
[Friedrich & Pinkal ACL 2015]

labels assigned to other

NPs/clauses influence the decisions



Accuracy: ACE-2 and ACE-2005



Few generic instances.

[Friedrich et al. LAW 2015]

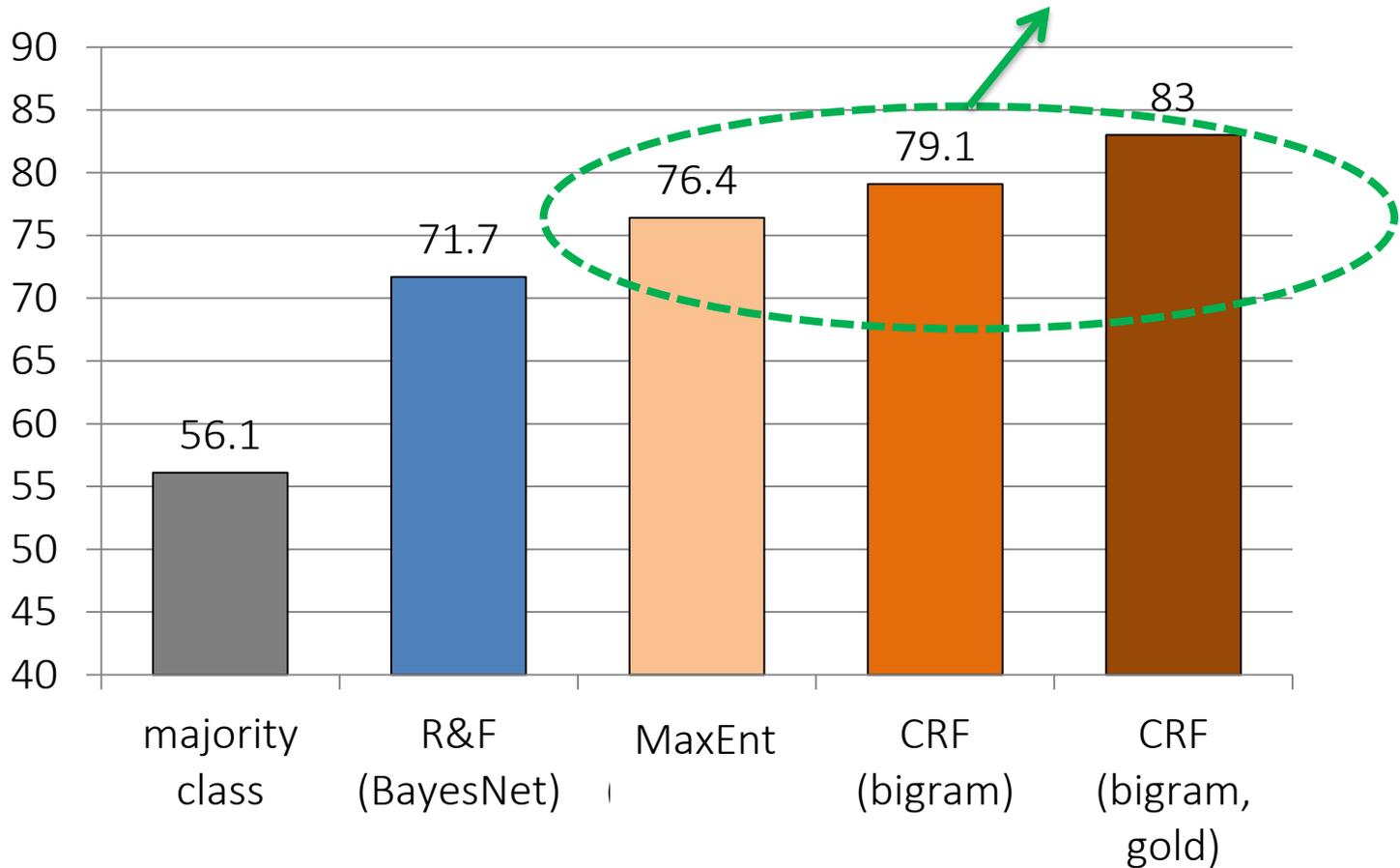
Problems in annotation guidelines, mix genericity and specificity.

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

Accuracy: Wikipedia data (main referent)



discourse / context information helps!



{generic, non-generic}

all differences statistically significant

Computational modeling of situation entity types



[ACL 2014]

lexical
aspectual
class

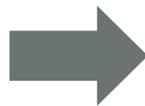
[EMNLP 2015]

recognize
habituality

[ACL 2015, LAW 2015]

is the main
referent generic?

entire
documents,
segmented
into clauses



automatic classification of
situation entity types

[ACL 2016]

Computational modeling of situation entity types



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[ACL 2015, LAW 2015]

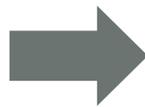
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automatic classification of situation entity types

[ACL 2016]



Lexical aspectual class



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



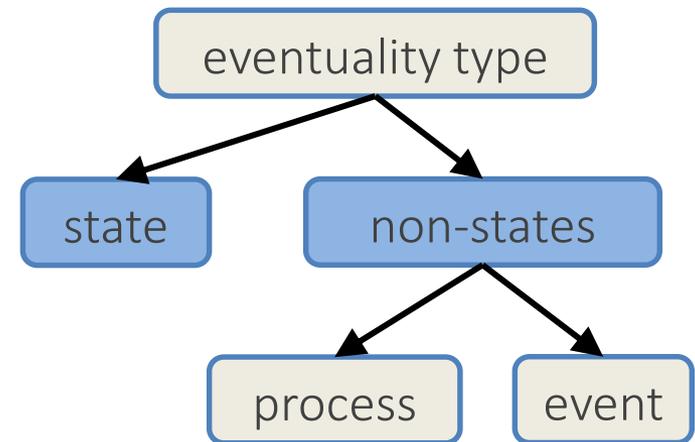
Juice **fills** the glass.
stative

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

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

states	<i>love, own</i>	stative
activities	<i>run</i>	dynamic
accomplishments	<i>write a letter</i>	
achievements	<i>realize</i>	

Bach [1986]: time schemata of sentences

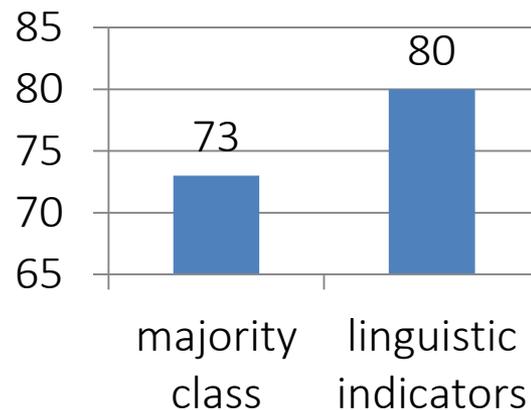




Predicting fundamental aspectual class

John will love this cake!	stative	<i>John love cake</i>
John has kissed Mary.	dynamic	<i>John kiss Mary</i>
John drives to work.	dynamic	<i>John drive to work</i>

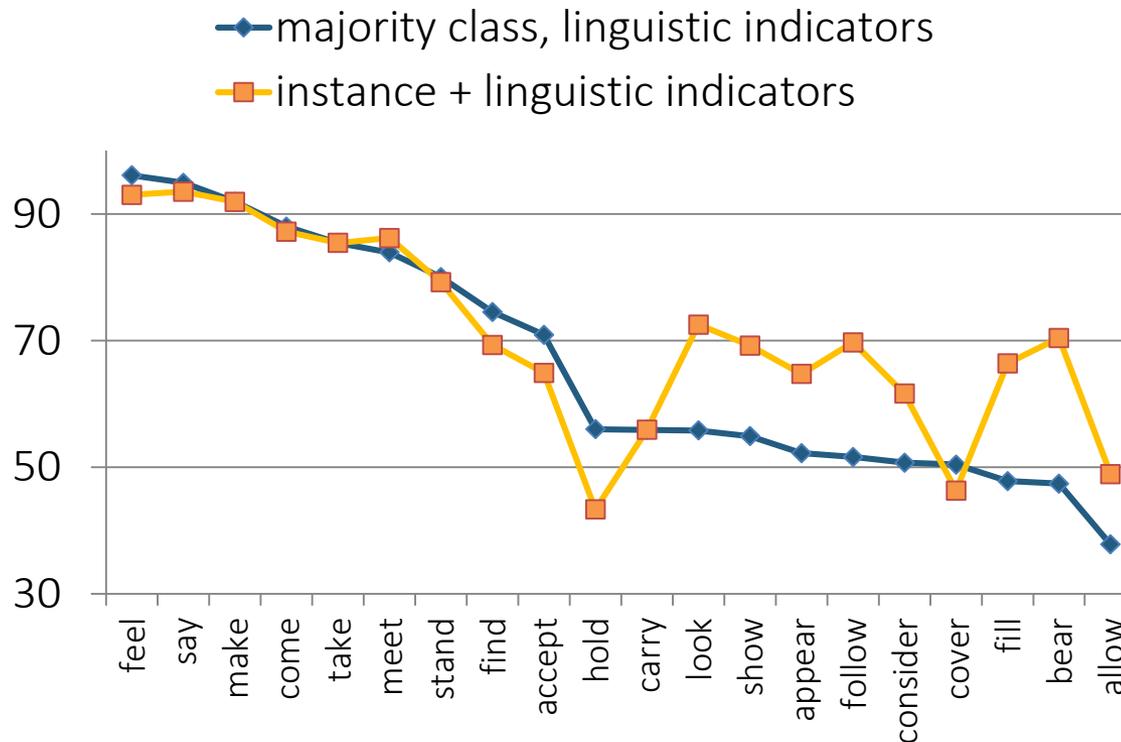
- **Features:** linguistic indicators → patterns how verb types behave in a large parsed corpus, e.g., how often they occur with the progressive, with certain adverbials, ... [Siegel & McKeown 2000]
- **Data set:** MASC letter, essays, news annotated for aspectual class on clause level: *The glass is **filled** with juice. stative*
- **Finding:** linguistic indicators generalize across verb types





Predicting fundamental aspectual class

- **Problem:** features are type-based → performance never better than guessing the majority class per verb type
- **Solution:** add in instance-based features (syntactic-semantic features reflecting context of each verb occurrence)



*Brown corpus
130 sentences per
verb type,
leave-one-out CV
labels: stative,
dynamic, both
readings possible*

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

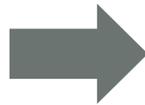
[EMNLP 2015]

is the main referent generic?

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automatic classification of situation entity types

[ongoing work]

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

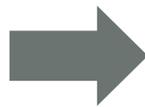
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automatic classification of situation entity types

[ACL 2016]



Habituality

episodic

a particular event

January						
				1	2	3
4	5	6	7	8	9	10
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25	26	27	28	29	30	31

John went swimming yesterday!

habitual

generalization over situations, exceptions are tolerated

January						
				1	2	
4	5	6	7	8	9	10
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25	26	27	28	29	30	31

Bill often goes swimming.

Bill likes coffee.
 Bill didn't go swimming.
 Bill can swim.



A three-way classification of clausal aspect



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

[Friedrich & Pinkal, EMNLP 2015]

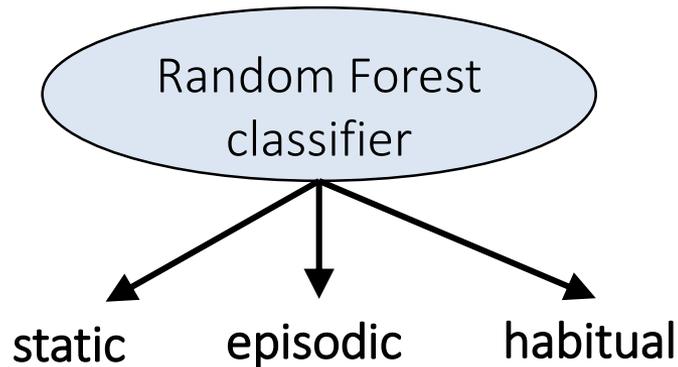


Automatic classification of clausal aspect

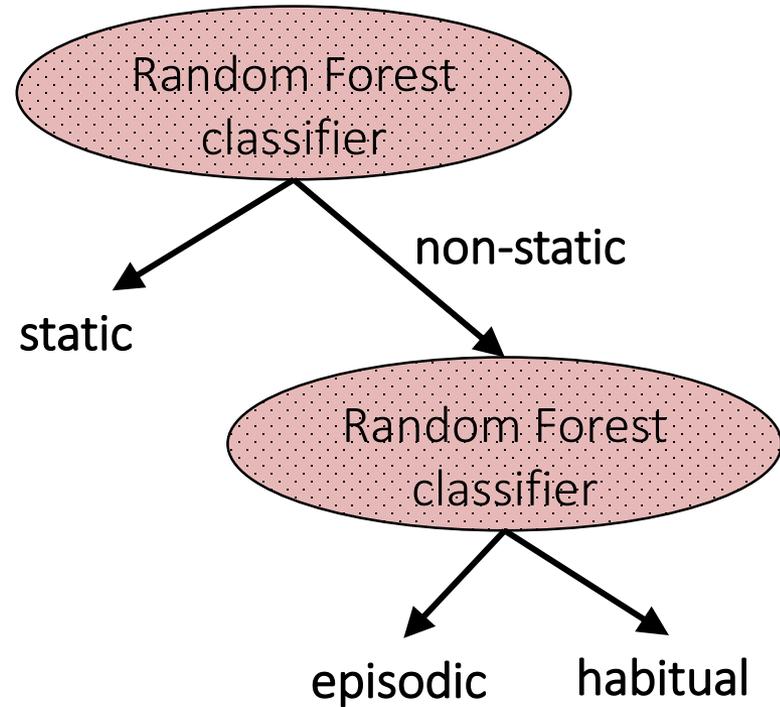
Features:

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

JOINT MODEL



CASCADED MODEL

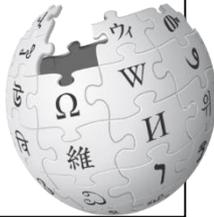


Automatic classification of clausal aspect



102 texts, 10355 clauses
3 annotators, $\kappa=0.61$

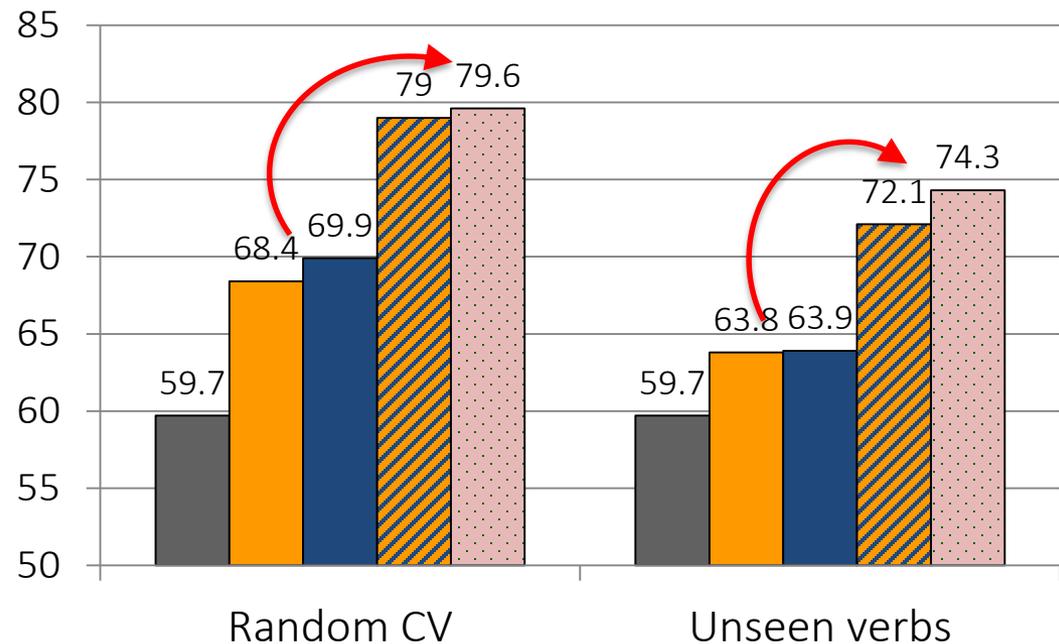
60% static
20% episodic
20% habitual



- maj. class
- instance-based
- Type
- instance+type
- CASCADED

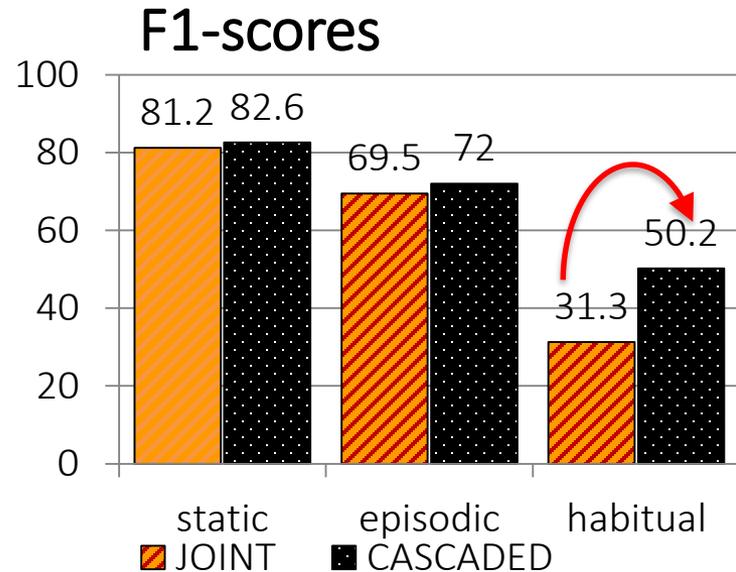
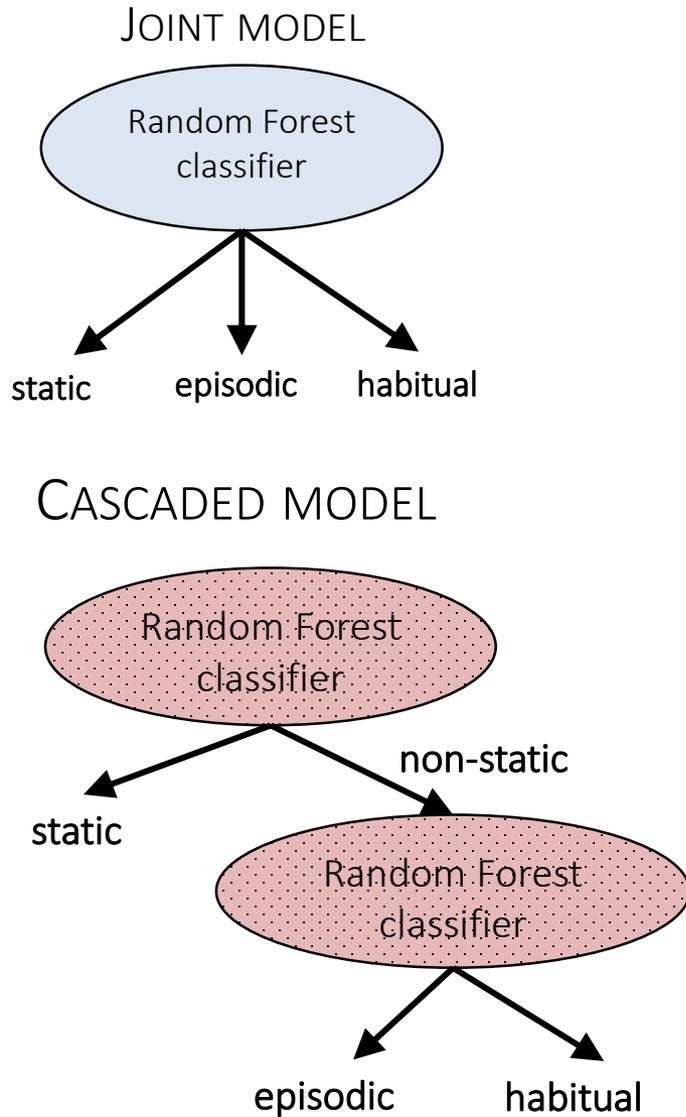
} JOINT

accuracy in %



Both instance- and type-based features are needed!

Automatic classification of clausal aspect



Cascaded model improves identification of habituals in free text.

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

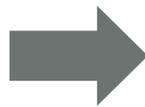
[EMNLP 2015]

is the main referent generic?

lexical aspectual class

recognize habituality

entire documents, segmented into clauses



automatic classification of situation entity types

[ACL 2016]

Computational modeling of situation entity types



[ACL 2014]

[ACL 2015, LAW 2015]

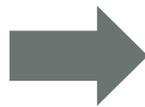
[EMNLP 2015]

is the main referent generic?

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entire documents, segmented into clauses



automatic classification of situation entity types

[ACL 2016]

Conditional random field (CRF)



- text document =
sequence of clauses
- \vec{y} = sequence of situation
entity type labels
- \vec{x} = features representing
the clauses

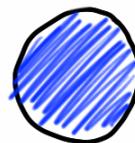
$$P(\vec{y}|\vec{x}) = \frac{1}{Z(\vec{x})} \exp \left(\sum_{j=1}^n \sum_{i=1}^m \lambda_i f_i(y_{j-1}, y_j, \vec{x}, j) \right)$$

EVENT

EVENT

STATE

\vec{y}



\vec{x}

Julie met
Cooper.

They quickly
became
friends.

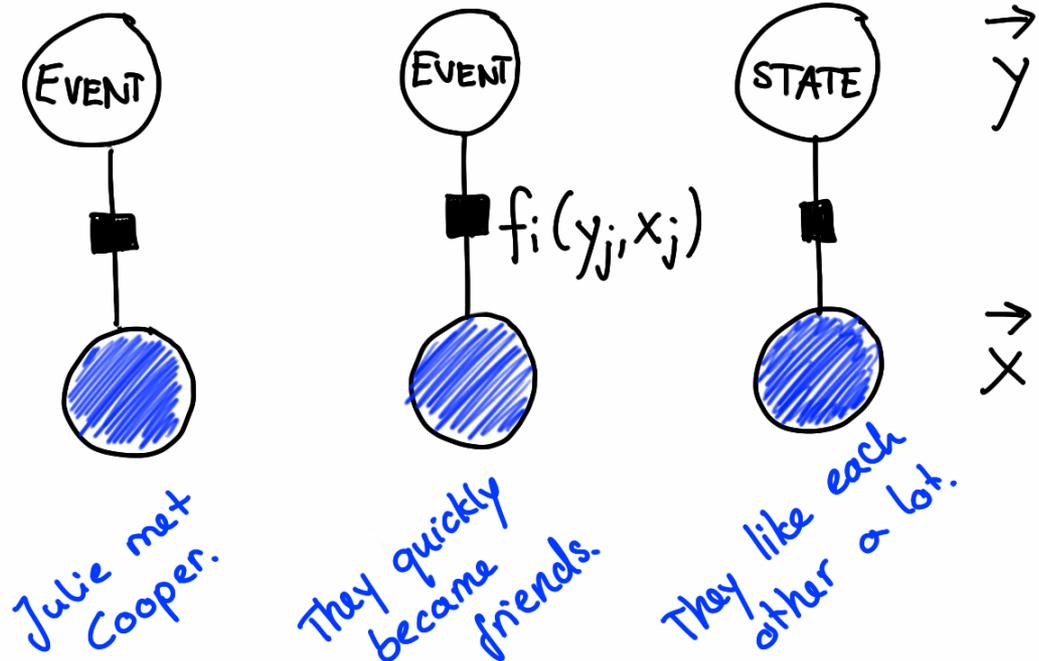
They like each
other a lot.

Conditional random field (CRF)



- text document = sequence of clauses
- \vec{y} = sequence of situation entity type labels
- \vec{x} = features representing the clauses
- λ_i = weight for feature function f_i
- $f_i(y_j, x_j)$ = clause / type
→ MaxEnt

$$P(\vec{y}|\vec{x}) = \frac{1}{Z(\vec{x})} \exp \left(\sum_{j=1}^n \sum_{i=1}^m \lambda_i f_i(y_{j-1}, y_j, \vec{x}, j) \right)$$

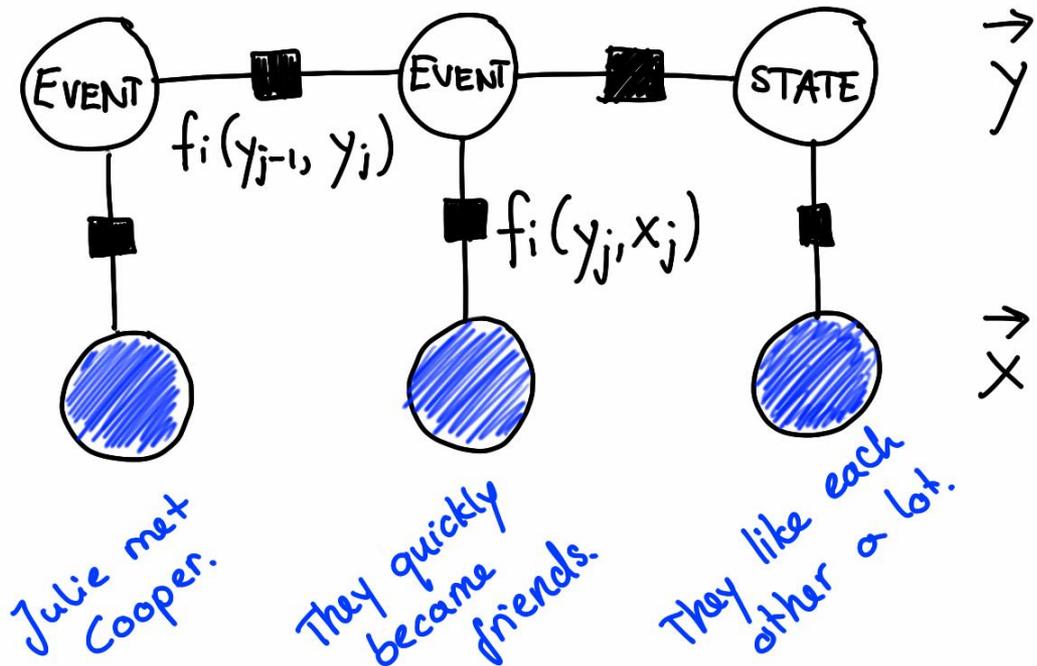




Conditional random field (CRF)

- text document = sequence of clauses
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- \vec{x} = features representing the clauses
- λ_i = weight for feature function f_i
- $f_i(y_j, x_j)$ = clause / type
→ MaxEnt
- $f_i(y_{j-1}, y_j)$ = type / type
→ CRF

$$P(\vec{y}|\vec{x}) = \frac{1}{Z(\vec{x})} \exp \left(\sum_{j=1}^n \sum_{i=1}^m \lambda_i f_i(y_{j-1}, y_j, \vec{x}, j) \right)$$



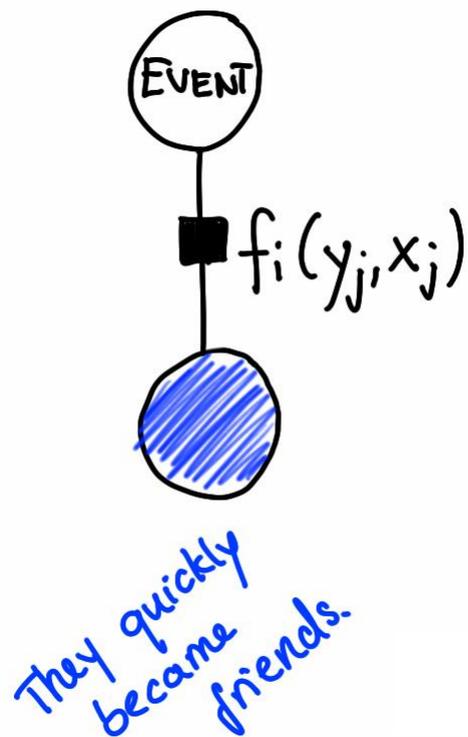
Situation entity types



- Which parts of the clause are most important to distinguish the types?
[Friedrich & Palmer 2014b], [Friedrich et al. 2015], [Smith 2003]

main verb	→ verb that heads the clause	
	Julie likes Cooper.	STATE
	Julie met Cooper.	EVENT
	Julie teases Cooper.	GENERALIZING SENTENCE
main referent	→ subject of main verb (what the clause is about)	
	Julie is an owl.	STATE
	Owls are nocturnal animals.	GENERIC SENTENCE

Features for clauses



- **pos:** part of speech tags
- **bc:** Brown word clusters
[Turian et al. 2010]
- **mv:** main verb
 - tense, voice, progressive, perfect, lemma, WordNet hypernyms, ...
- **mr:** main referent
 - lemma, determiner type, noun type, number, person, countability, WordNet, dependency relations, ...
- **cl:** *clause*
 - adverbs, conditional, modal, negated, ...



How well does it work?

Results: Impact of different feature sets



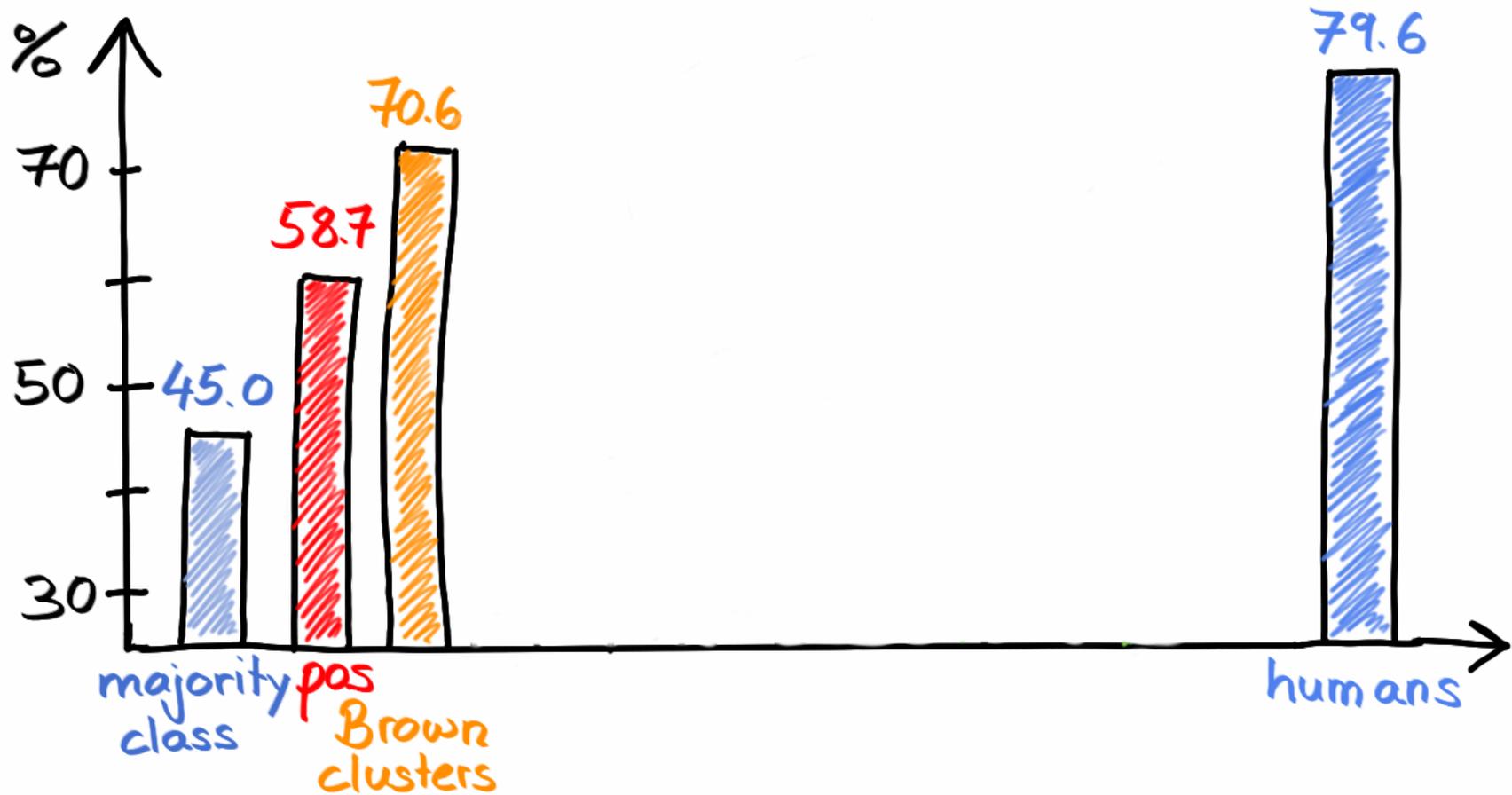
- Accuracy. Wiki+MASC dev set (80% of data), CRF, 10-fold CV.





Results: Impact of different feature sets

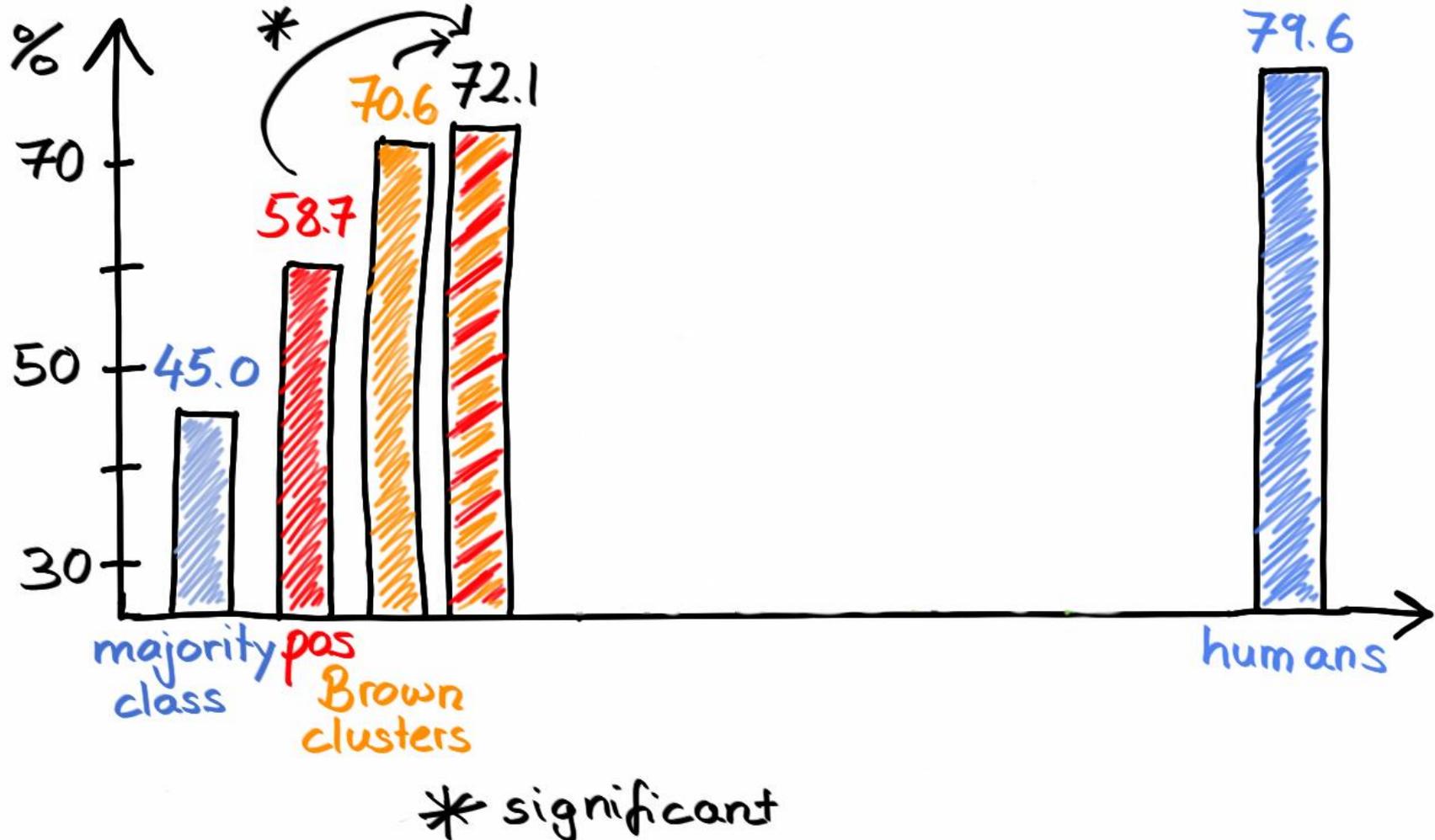
- Accuracy. Wiki+MASC dev set (80% of data), CRF, 10-fold CV.





Results: Impact of different feature sets

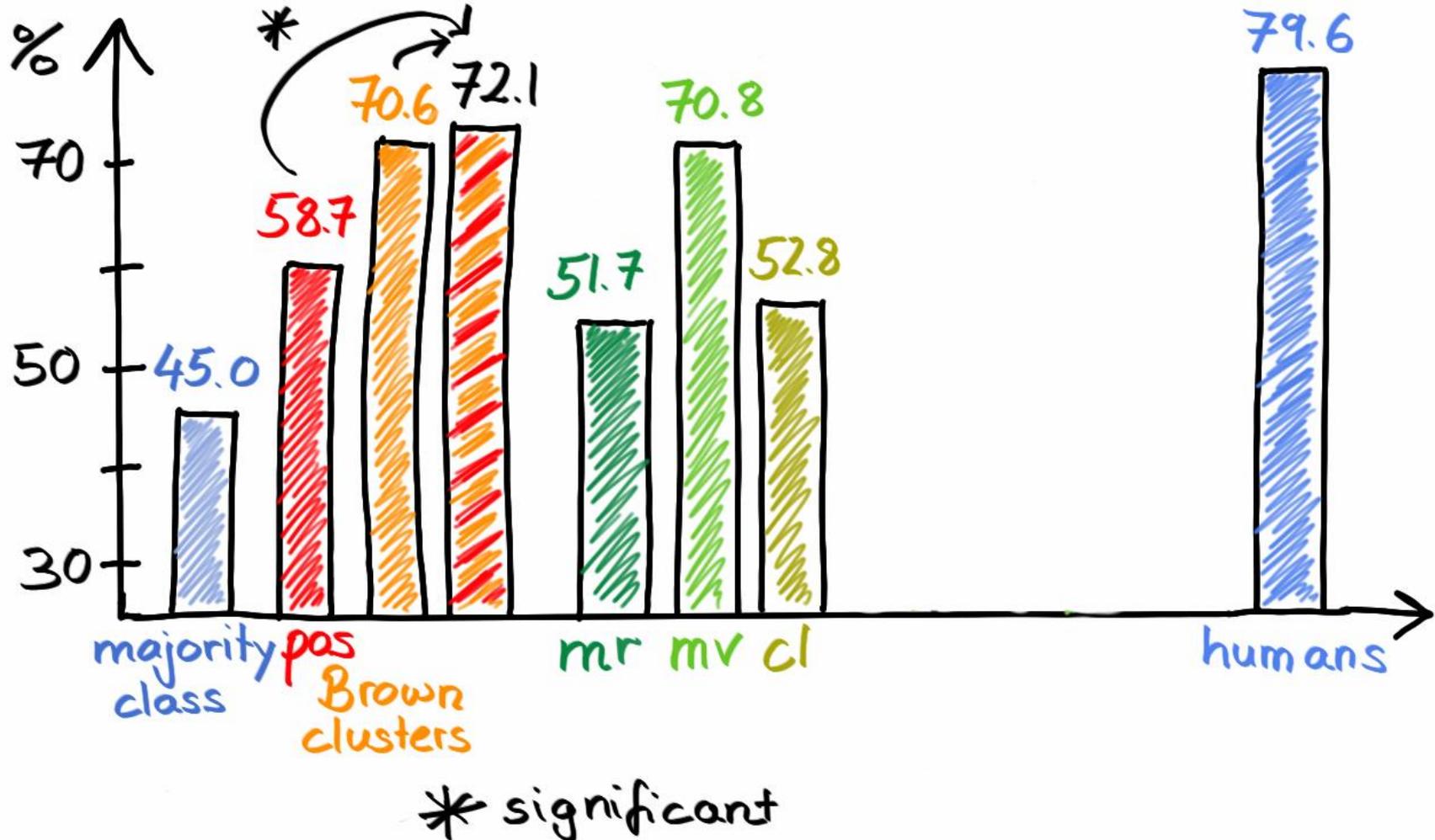
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Results: Impact of different feature sets

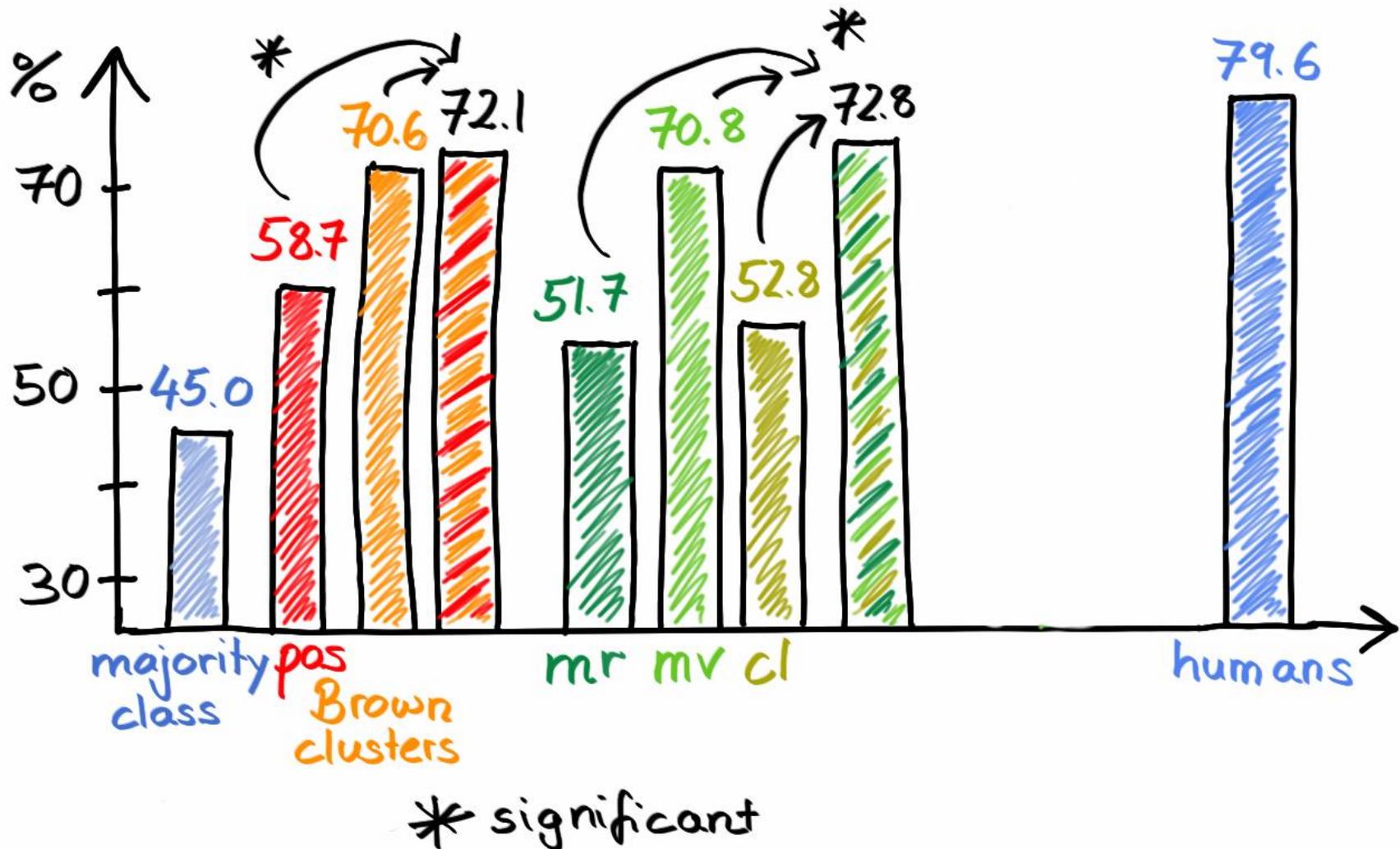
- Accuracy. Wiki+MASC dev set (80% of data), CRF, 10-fold CV.





Results: Impact of different feature sets

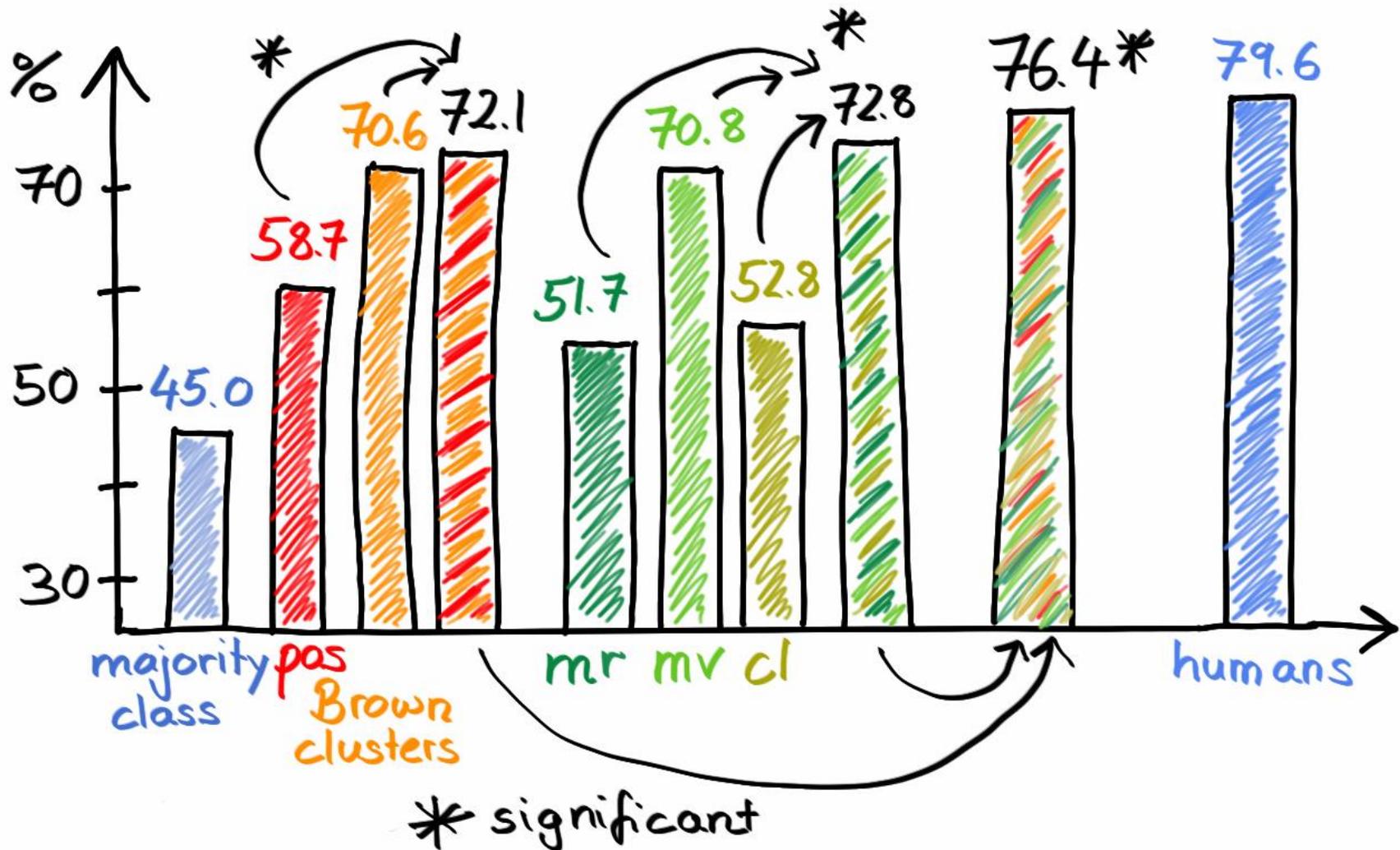
- Accuracy. Wiki+MASC dev set (80% of data), CRF, 10-fold CV.





Results: Impact of different feature sets

- Accuracy. Wiki+MASC dev set (80% of data), CRF, 10-fold CV.



Results on heldout test set (20% of data)



- Training on entire MASC+Wiki development set.

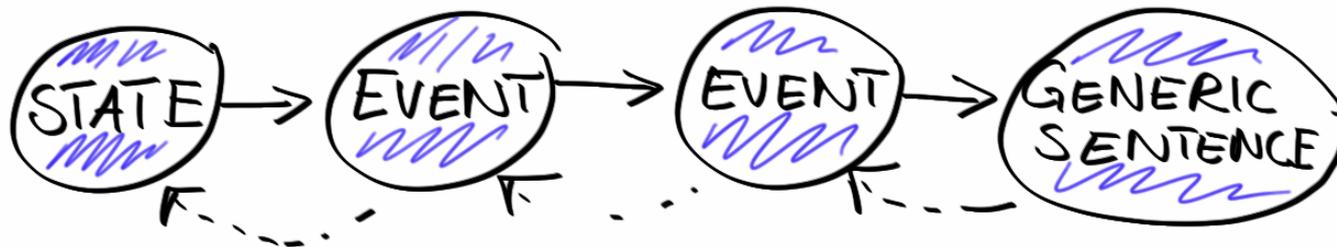
feature set	macro-average			accuracy
	P	R	F	
majority class (STATE)	6.4	14.3	8.8	44.7
pos+Brown	67.6	60.6	63.9	69.8
mr+mv+cl	69.9	61.7	65.5	71.4
all	73.4	65.5	69.3	74.7

Is sequential information important?



as claimed by Palmer et al. [ACL 2007]

... and if yes, when?



Maximum entropy model vs. conditional random field



situation entity type	MaxEnt	CRF
STATE	79.1	80.6
EVENT	77.5	78.6
REPORT	78.2	78.9
GENERIC SENTENCE	61.3	68.3
GENERALIZING SENTENCE	25.0	29.4
IMPERATIVE	72.3	75.3
QUESTION	84.4	84.4
macro-avg. F1	68.7	71.2
accuracy	74.1	76.4

↙
significant

How genre-dependent is this task?



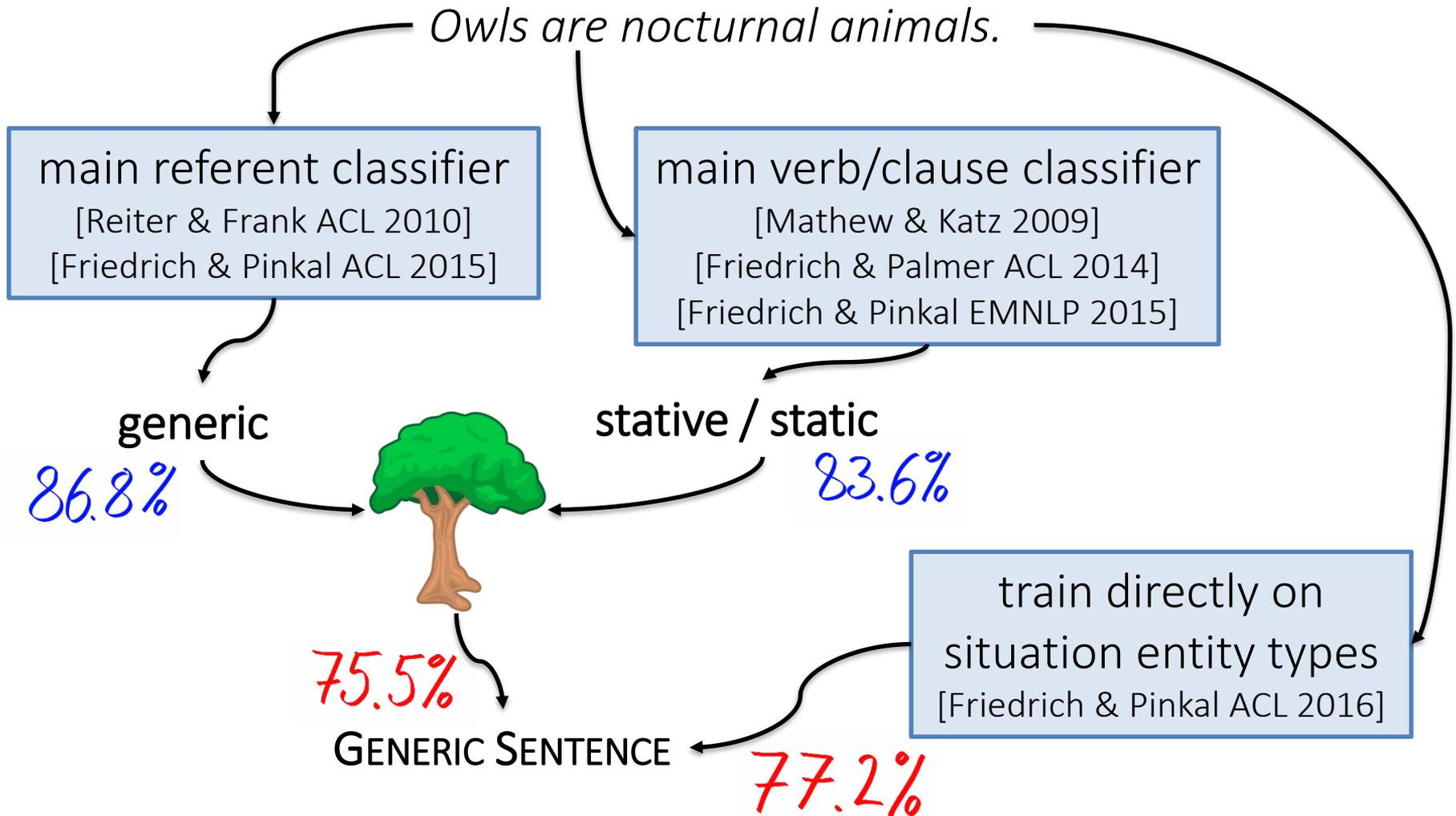
fiction
jokes
wikipedia
technical
govt-docs
blog
letters
email
ficlets
journal
travel

- How important is it to have in-genre training data?
 - helpful, $\approx + 5\%$ accuracy / F1
- Is it a good idea to add out-of-genre training data?
 - YES! 49.0 \rightarrow 64.0 (macro-average F1)
 - system gets better at identifying infrequent types
- Statistics per type / genre: see [Friedrich, Palmer & Pinkal ACL 2016]

Pipelined model for situation entity types?



- STATE, EVENT, GENERIC SENTENCE, GENERALIZING SENTENCE



Lessons learned



- situation entity type classification task is (somewhat) difficult even for humans
- system performs well when comparing to human performance (76% vs. 80%)
- our system performs well across genres
- some types are infrequent in particular genres
 - adding out-of-domain training data helps to identify them
- a wide range of syntactic-semantic features are useful for this task
- sequential information useful for identifying „generic contexts“

Open questions



- integration of aspectual information into temporal relation identification systems?
- leveraging modeling of aspect for MT?
- semi-/unsupervised acquisition of aspectual information, e.g., from parallel corpora? **deep learning?**
- crowdsource relevant annotations?
- pre-processing step for argumentation mining, user-guided summarization etc.?