

Annotation and automatic classification of situation entity types

Annemarie Friedrich

joint work with Alexis Palmer

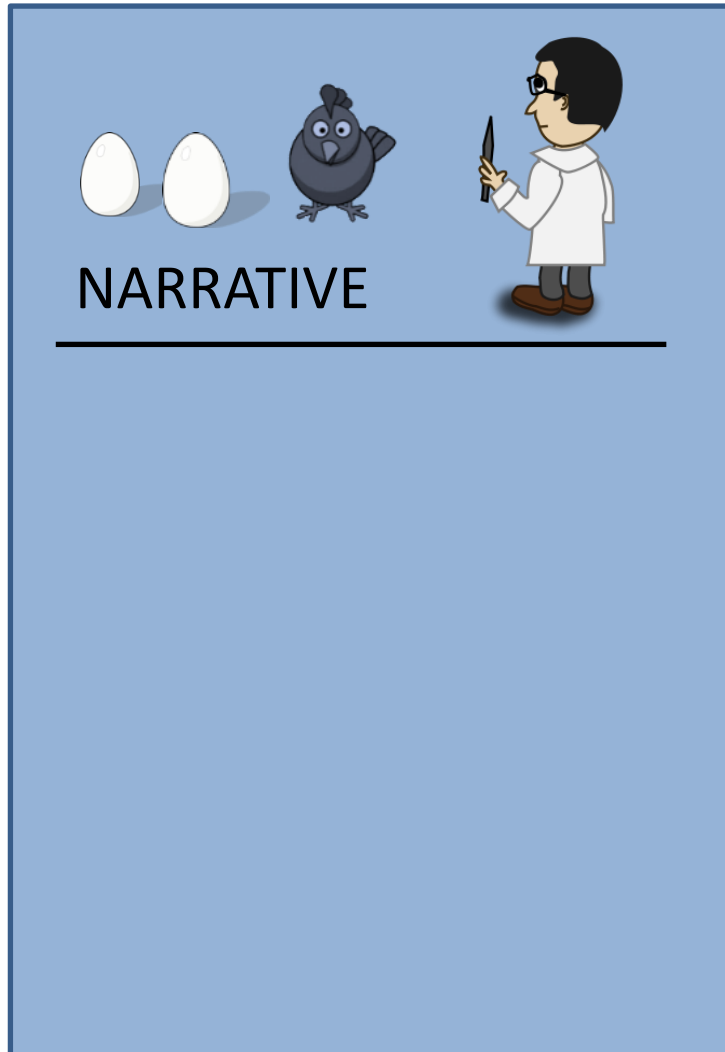
Department of Computational Linguistics
Saarland University

Situation entity types [Smith 2003]

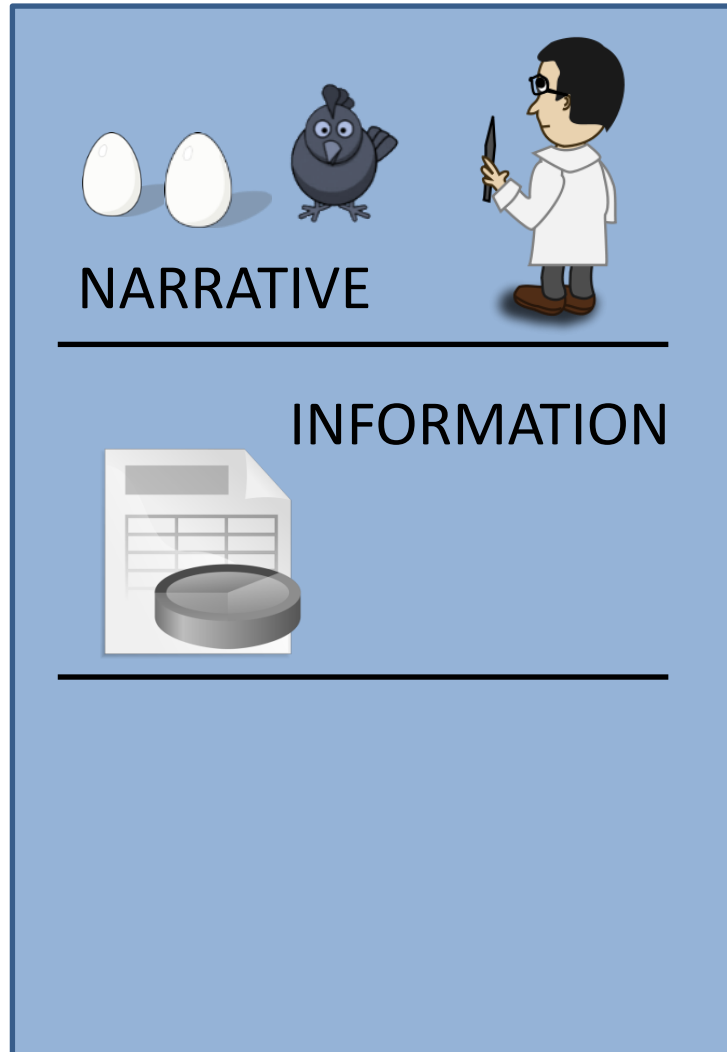
- clauses introduce situations to a discourse
- classification of types of situation (entities)

SE type	<i>Example</i>
STATE	<i>Mary likes cats.</i>
EVENT	<i>Mary fed the cats.</i>
GENERALIZING SENTENCE	<i>Mary often feeds my cats.</i>
GENERIC SENTENCE	<i>Cats are always hungry.</i>

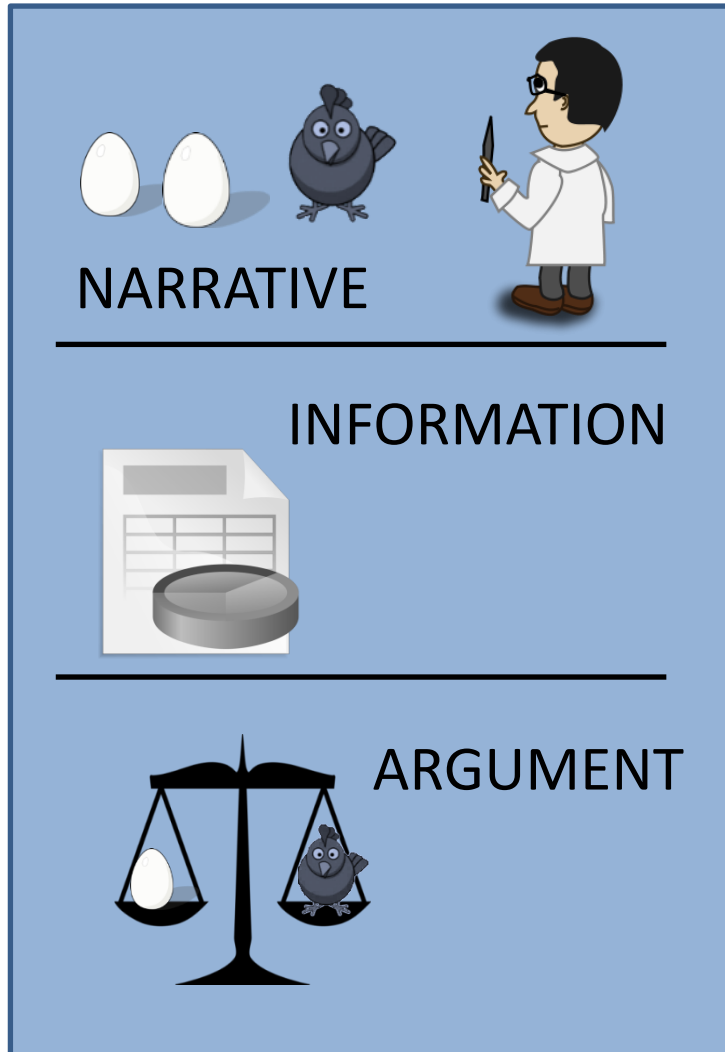
Modes of discourse [Smith 2003]



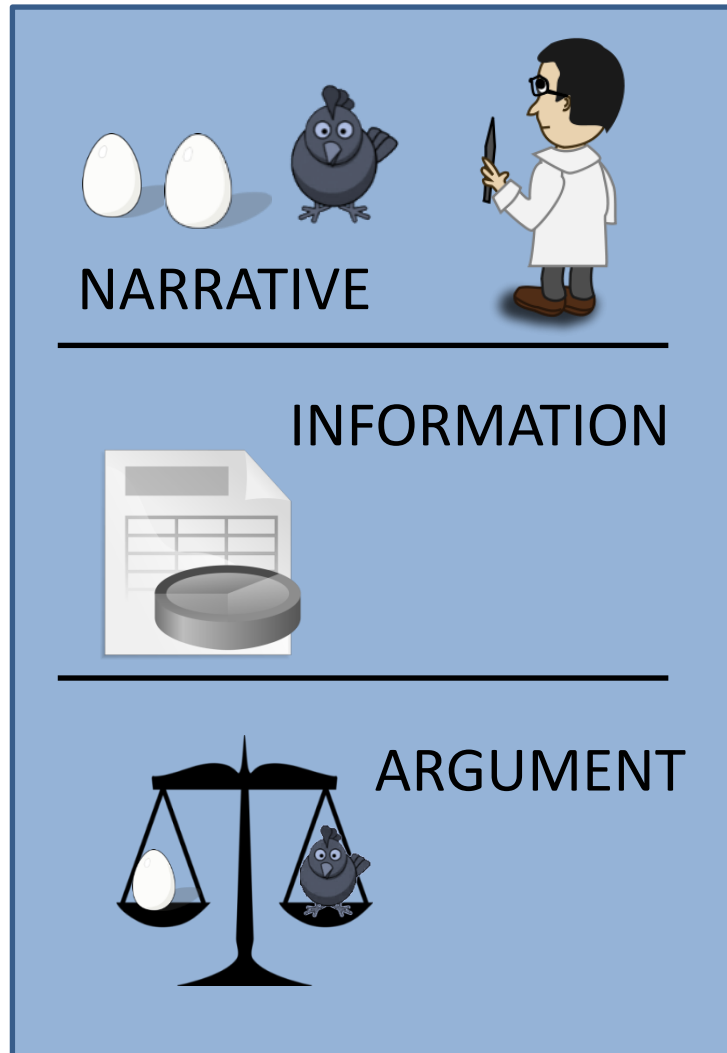
Modes of discourse [Smith 2003]



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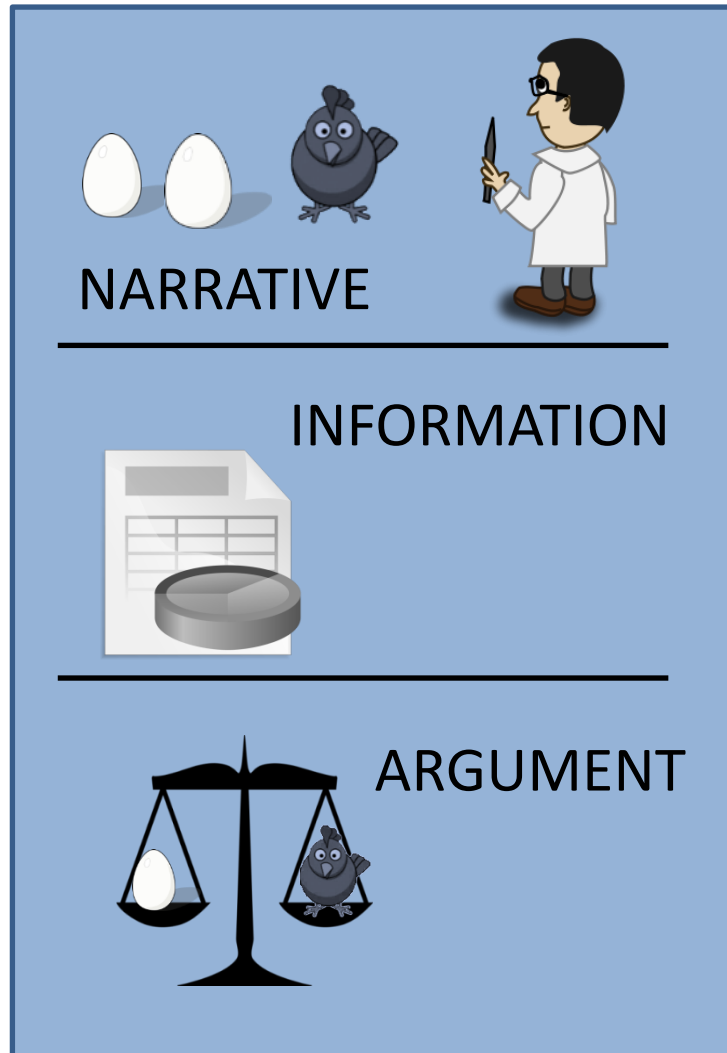


Modes of discourse [Smith 2003]



Different passages of a text can have different discourse modes.

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

related: Werlich's typology of texts (1975)

Modes of discourse [Smith 2003]

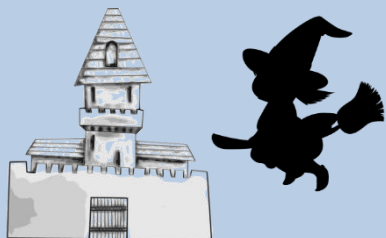


temporal progression

**EVENT,
STATE**

Modes of discourse [Smith 2003]

NARRATIVE



temporal progression

**EVENT,
STATE**

REPORT



temporal progression,
related to speech time

**EVENT, STATE,
general statives**

Modes of discourse [Smith 2003]

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temporal progression

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**EVENT, STATE,
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DESCRIPTION

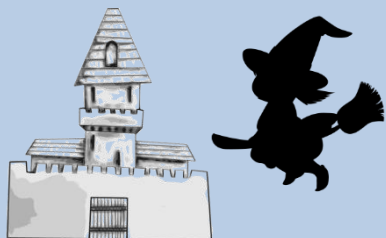


spatial progression

**EVENT, STATE,
ongoing EVENT**

Modes of discourse [Smith 2003]

NARRATIVE



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INFORMATION

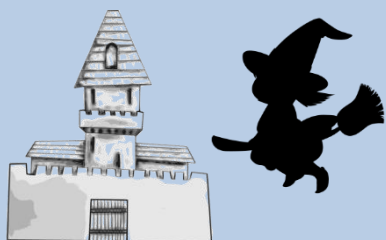


**general
statives**

atemporal, metaphoric progression

Modes of discourse [Smith 2003]

NARRATIVE



temporal progression

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spatial progression

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INFORMATION



**general
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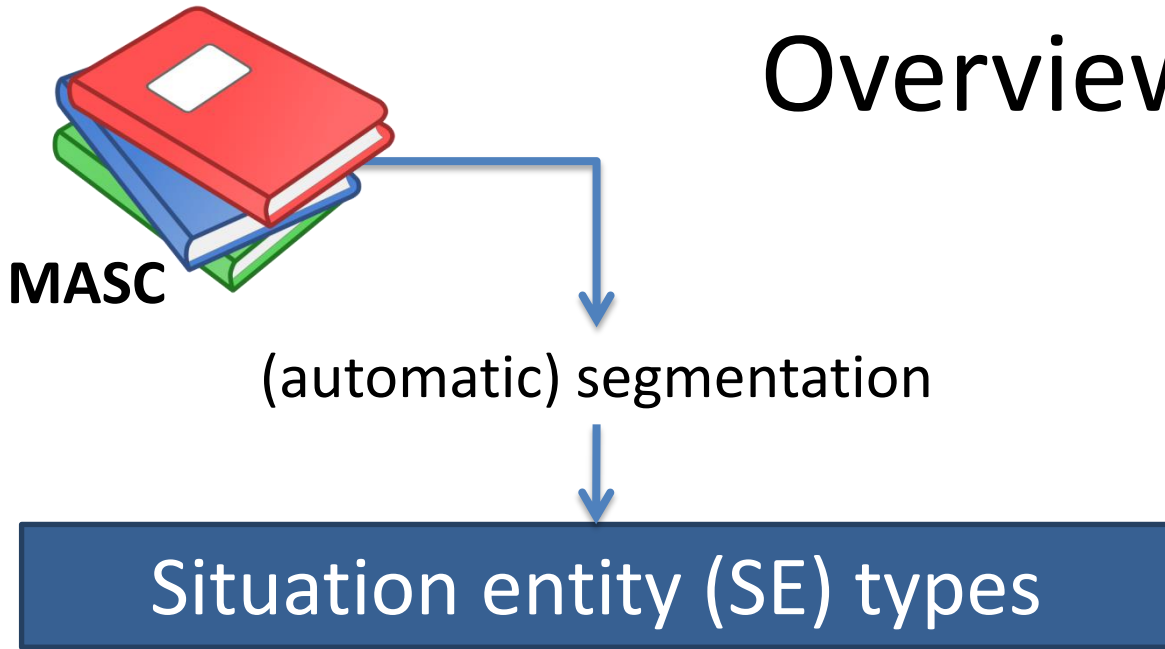
ARGUMENT



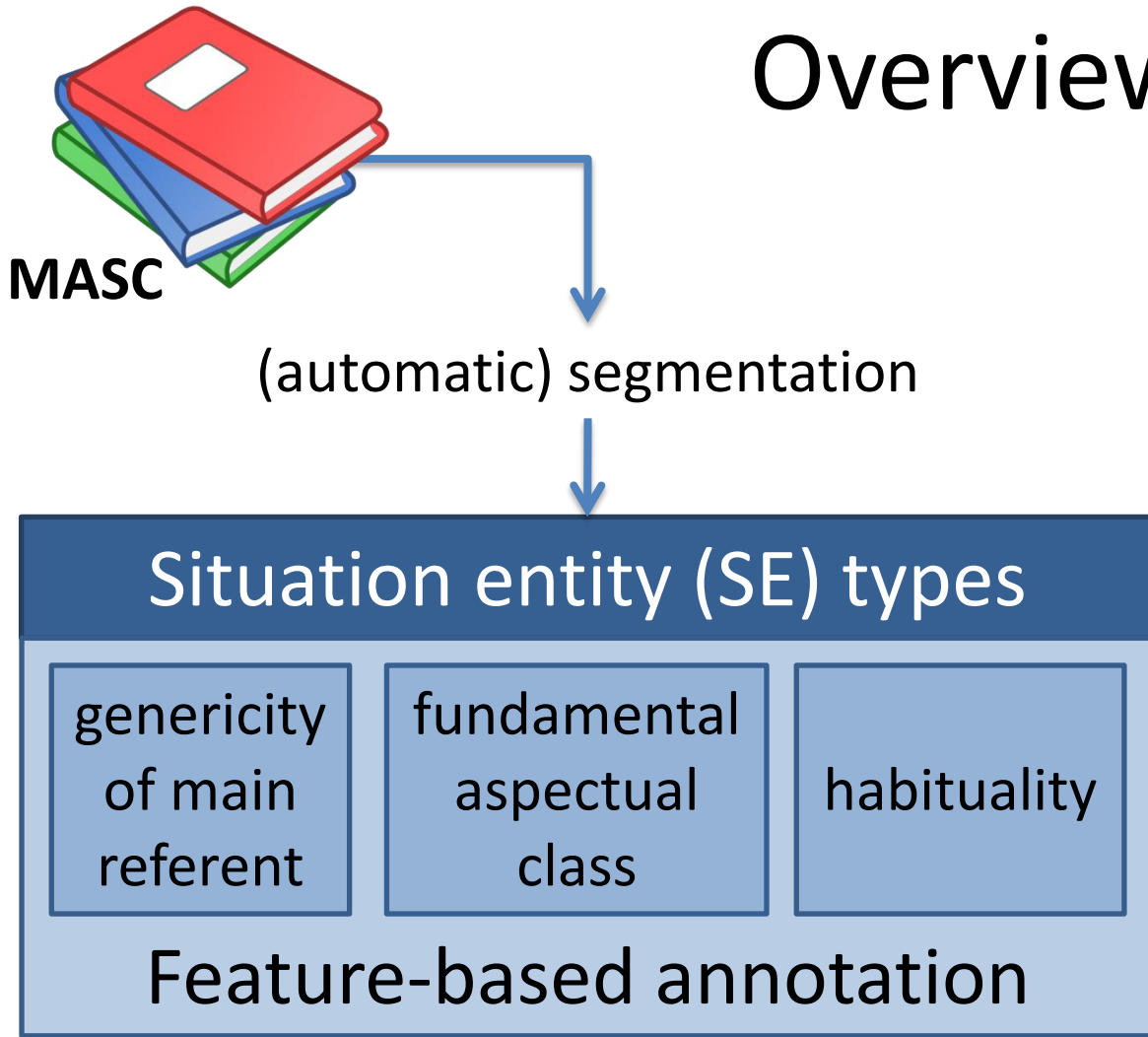
**FACT,
PROPOSITION,
general statives**

atemporal, metaphoric progression

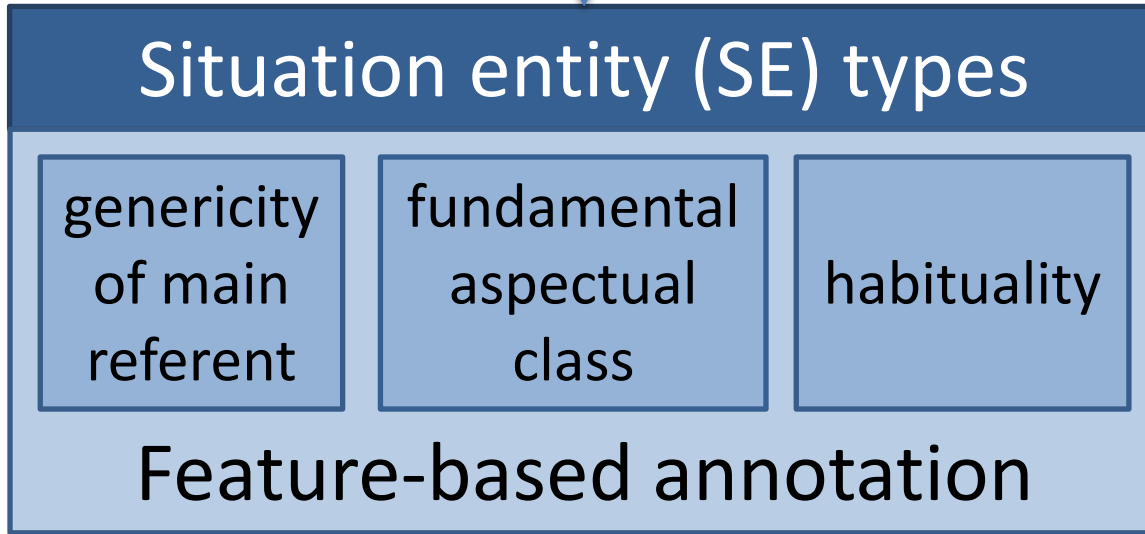
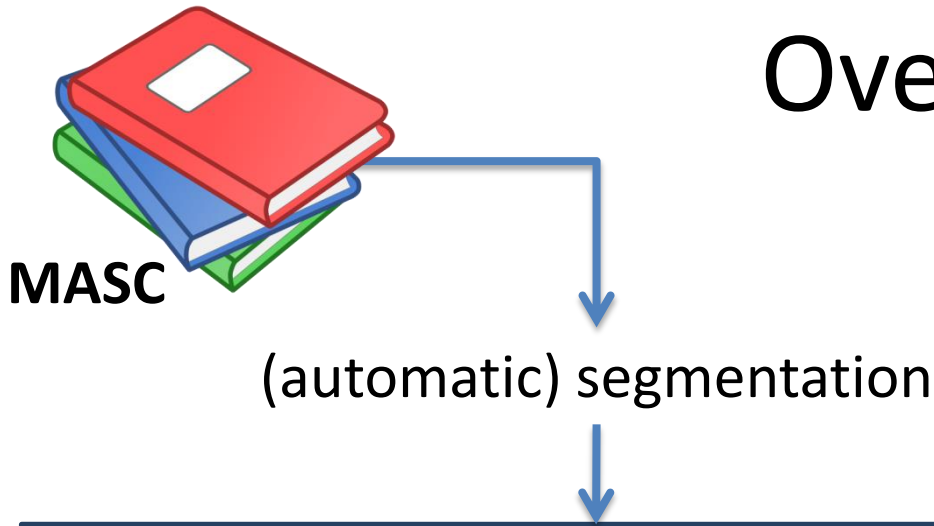
Overview



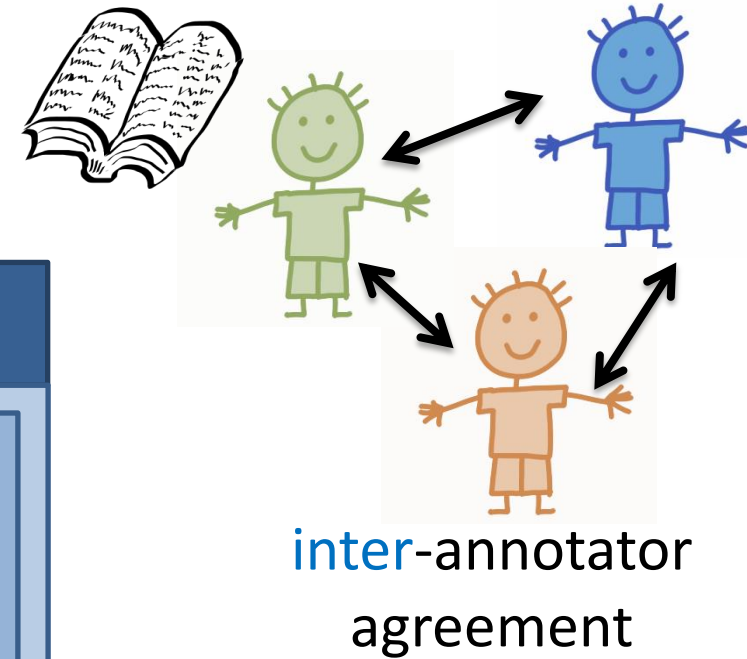
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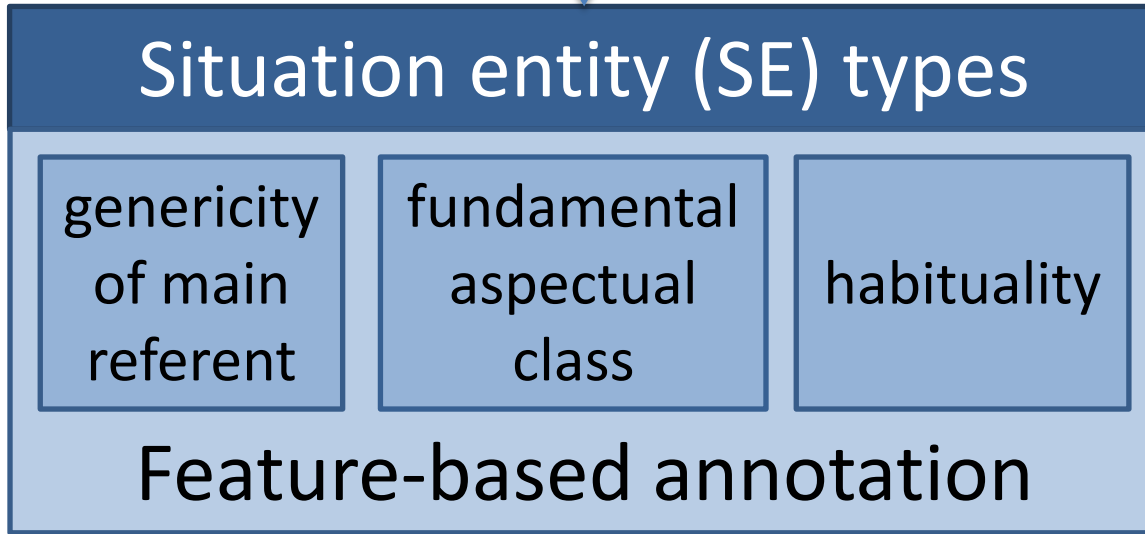
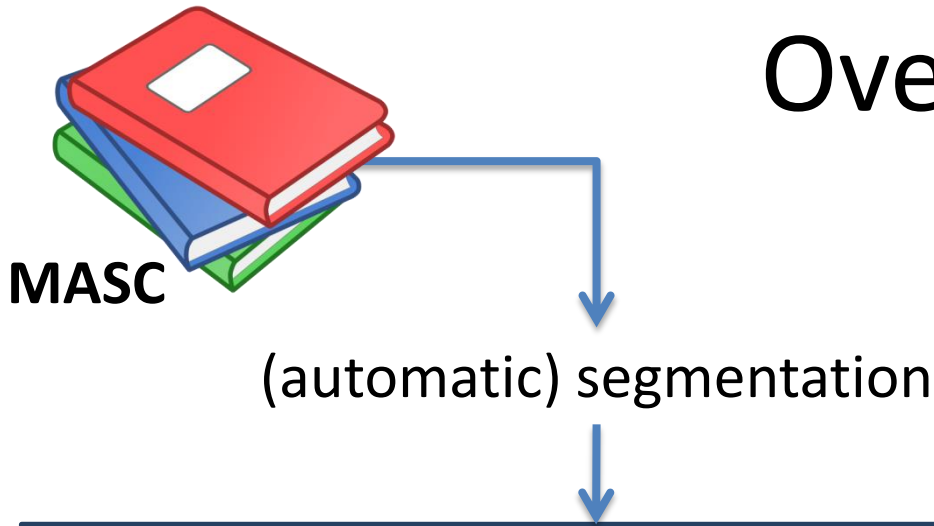
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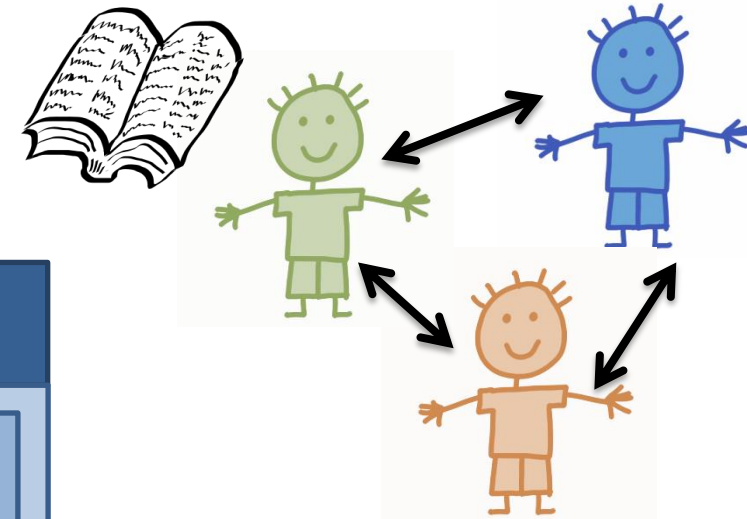
1) Corpus annotation



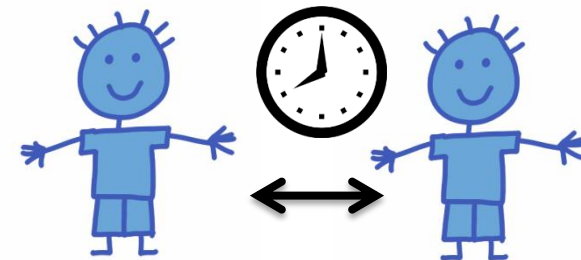
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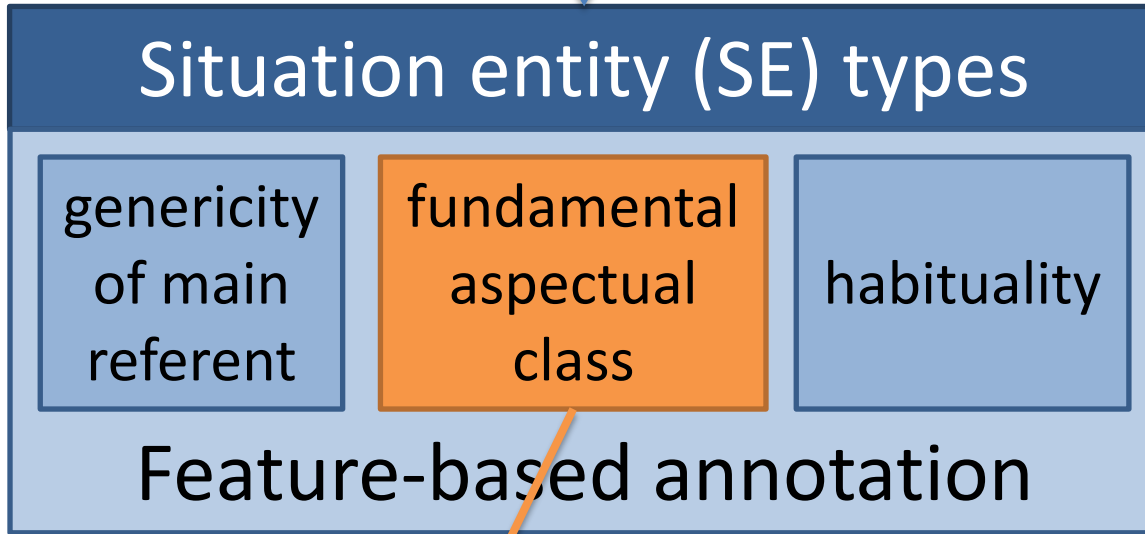
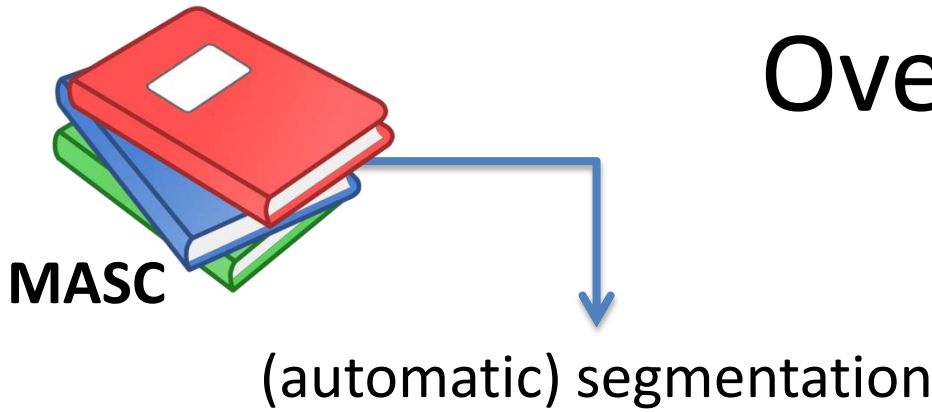


inter-annotator
agreement

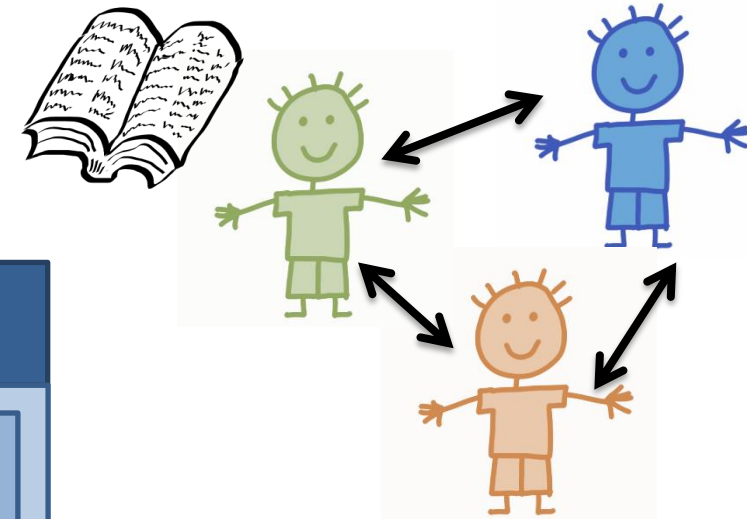


intra-annotator
consistency

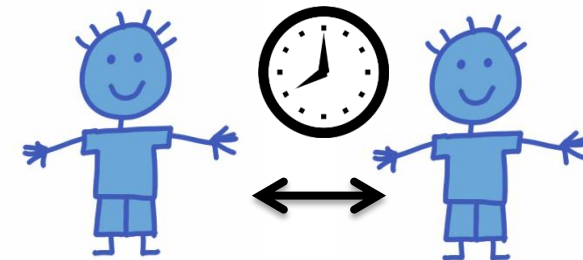
Overview



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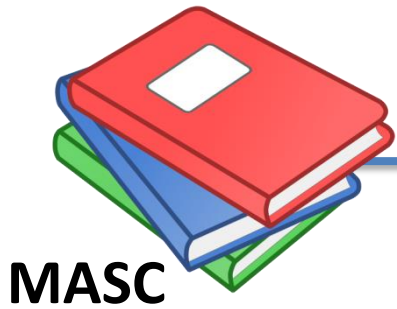
inter-annotator agreement



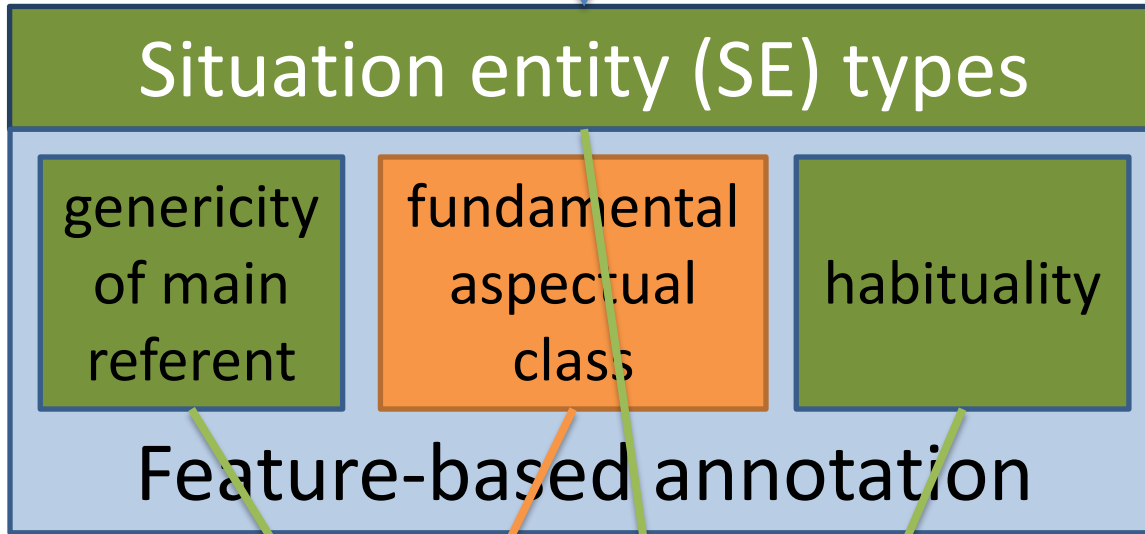
intra-annotator consistency

2) automatic classification

Overview



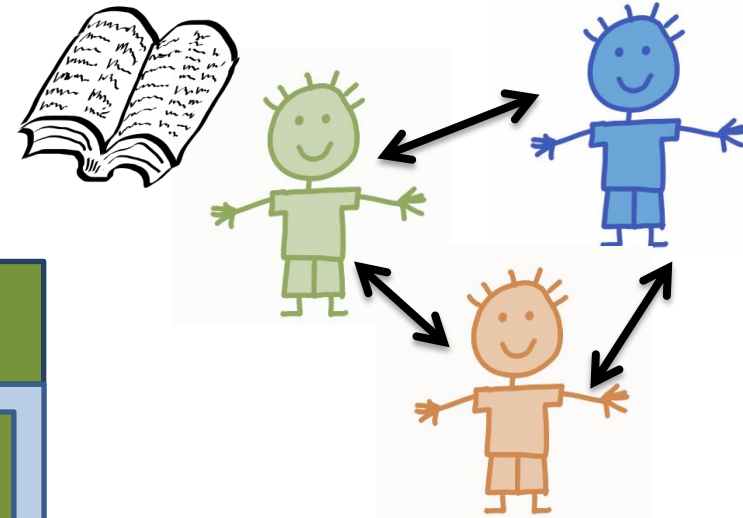
(automatic) segmentation



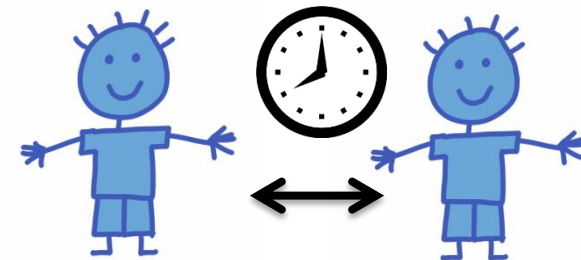
2) automatic classification

3) current status, ongoing & future work

1) Corpus annotation



inter-annotator
agreement



intra-annotator
consistency

Motivation of annotation study

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

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training, development, evaluation of
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foundation for analysis of the theory of
Discourse Modes [Smith 2003]

Situation entity types (SE types)

EVENT



Yesterday, Mary bought a cat.

Now she owns four cats.

Susie often feeds Mary's cats.

Cats are very social animals.

Situation entity types (SE types)

Yesterday, Mary bought a cat. **EVENT**

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STATE



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Situation entity types (SE types)

Yesterday, Mary bought a cat. **EVENT**

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} eventualities

Susie often feeds Mary's cats. **GENERALIZING
SENTENCE**

Cats are very social animals. **GENERIC
SENTENCE**

} general
statives

SE types: abstract entities

here: clausal complements
of factive / implicative verbs

Susie **knows** **STATE**

that Mary loves her cats a lot. **FACT** objects of
knowledge

SE types: abstract entities

here: clausal complements
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Susie **knows** **STATE**

that Mary loves her cats a lot. **FACT** objects of
knowledge

Susie **believes** **STATE**

that the cats also love Mary. **PROPOSITION**
objects of belief

SE types: speech act types [Palmer et al. 2007]

Did you see my cats? **QUESTION**

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

Derived situation entity types

coerce **EVENTs** to **STATEs**:

negation, modality, future / perfect tense,
conditionality, subjectivity

Susie **will** feed the cats.

Susie **has not fed** the cats.

If Susie has forgotten the cats,
they **might** be hungry now.

Derived SE types

general statives are not subject to such coercion:

Susie **never** feeds Mary's cats. **GENERALIZING
SENTENCE**

Cats **might** be the most popular pet. **GENERIC
SENTENCE**

SE 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 <u>that Mary fed the cats.</u>
	PROPOSITION	I believe <u>that Mary fed the cats.</u>
Speech Acts	QUESTION	Does Mary like cats?
	IMPERATIVE	Don't forget to feed the cats!

Related work

- Palmer et al. [2007]:
 - first labeled data set for SEs
 - ~6000 clauses
 - no annotation manual
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- Stede & Peldzsus [2012]:
 - illocutionary status of clauses in causal relations
~pragmatic role, e.g. REPORT, DIRECTIVE, COMMITMENT

Data: Manually Annotated SubCorpus (MASC) of Open American National Corpus

[Ide et al. 2008]

- ✓ additional types of annotation available
- ✓ open distribution of annotations
- ✓ wide range of genres

MASC section	# of situations (segments)	average # tokens per segment
news	3455	9.9
jokes	2563	6.9
letters	1851	11.1

annotation
status
LAW 2014

Segmentation

SPADE [Soricut & Marcu 2003]

+ heuristic post-processing

+ manual correction

Segmentation

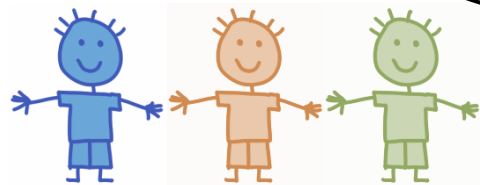
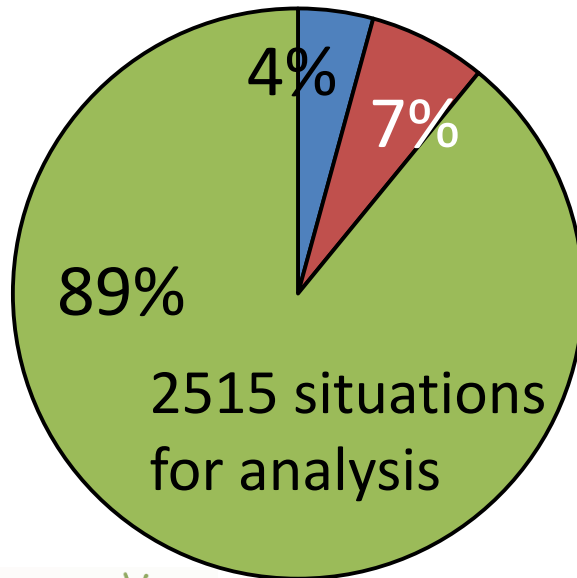
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by at least one annotator
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MASC news: 2823 segments

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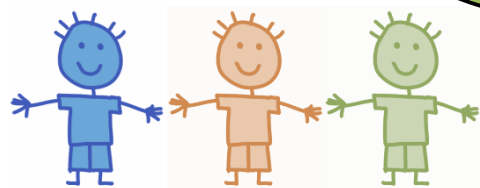
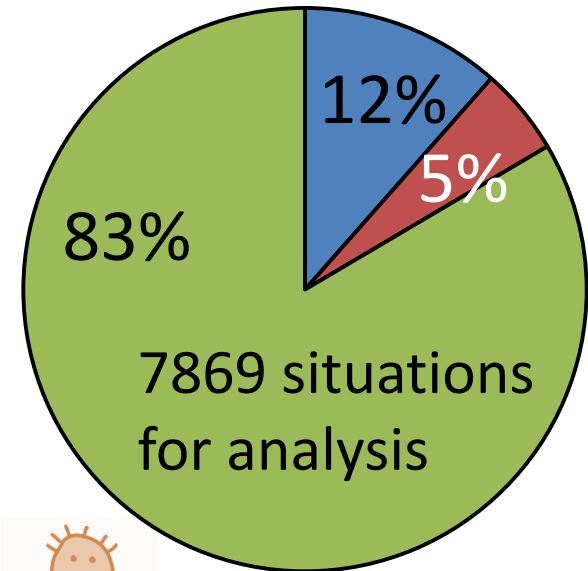
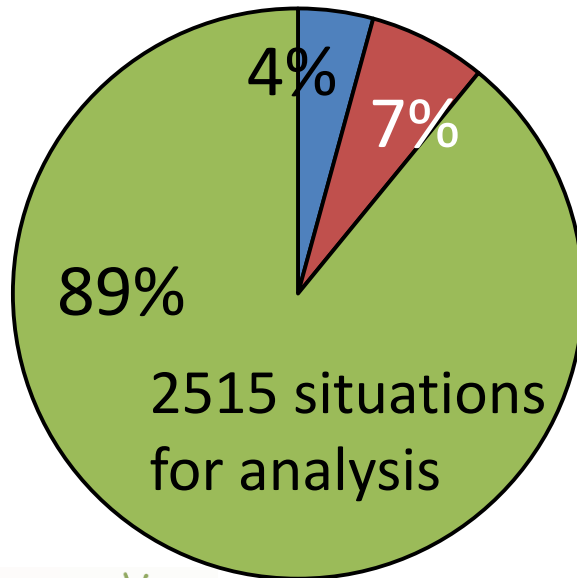
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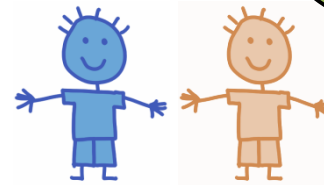
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marked as **NO SITUATION**
by at least one annotator
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merged to other segment
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MASC news: 2823 segments



MASC news, jokes, letters:
9428 segments

Feature-driven annotation

- 1 label “easy” cases: speech acts, lexically-triggered abstract entities, other clear-cut cases

Feature-driven annotation

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❷ determine **feature values**

genericity of main referent	fundamental aspectual class	habituality
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Which features distinguish the SE types from each other?

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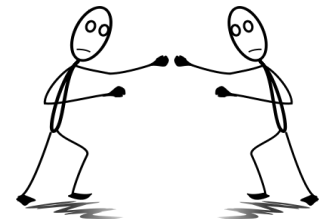
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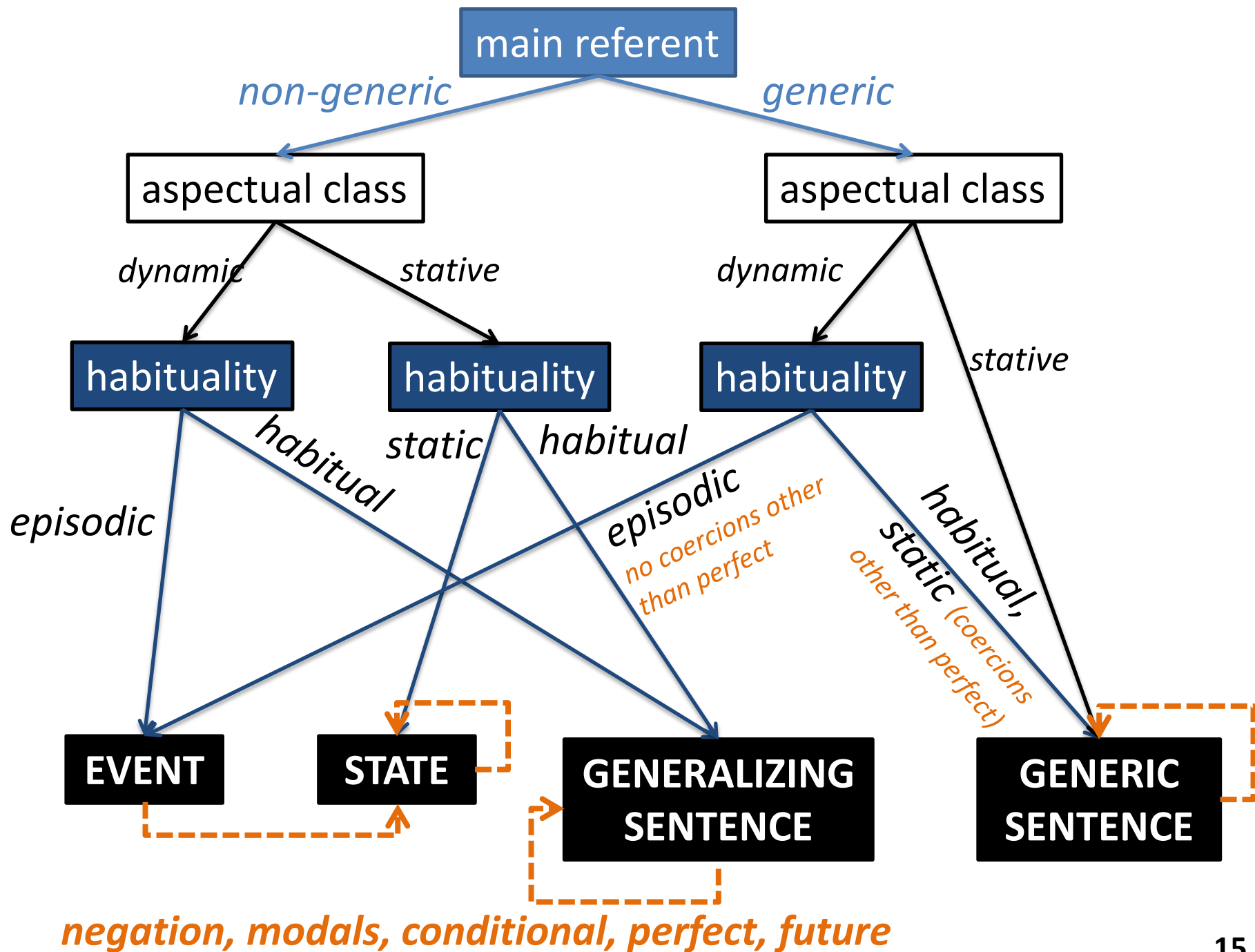


get partial
information



analyze
disagreements





Feature: genericity of main referent

What is this clause about? → usually the grammatical subject

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What is this clause about? → usually the grammatical subject

NON-GENERIC

particular entity / group /
company / organization /
situation / process

Mary likes cats.

The cats broke the TV.

WWF protects animals.

That she didn't answer upset me.

Knitting this scarf took me two days.

Feature: genericity of **main referent**

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GENERIC

**kind-referring / class-
referring NPs**
generic concepts

Cats eat mice.

Lions in captivity have trouble
to produce offspring.

Dinosaurs are extinct.

Security is an important issue.

Knitting a scarf is generally fun.

Feature: genericity of main referent

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distinguishes GENERIC SENTENCES from other SE types
(in combination with other features)

Feature: fundamental aspectual class

*feature of the entire clause,
marks main verb.*

Feature: fundamental aspectual class

distinguishes
EVENTs from STATEs

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Juice **fills** the glass.
STATIVE

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

Feature: fundamental aspectual class

distinguishes
EVENTs from STATEs

*feature of the entire clause,
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Juice **fills** the glass.
STATIVE

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



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

Feature: **habituality**

*feature of the entire clause,
marks main verb.*

distinguishes EVENTS
from general statives.

Feature: **habituality**

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distinguishes EVENTS
from general statives.

Mary fed her cats this morning.

episodic: one-time event

Mary feeds her cats every morning.

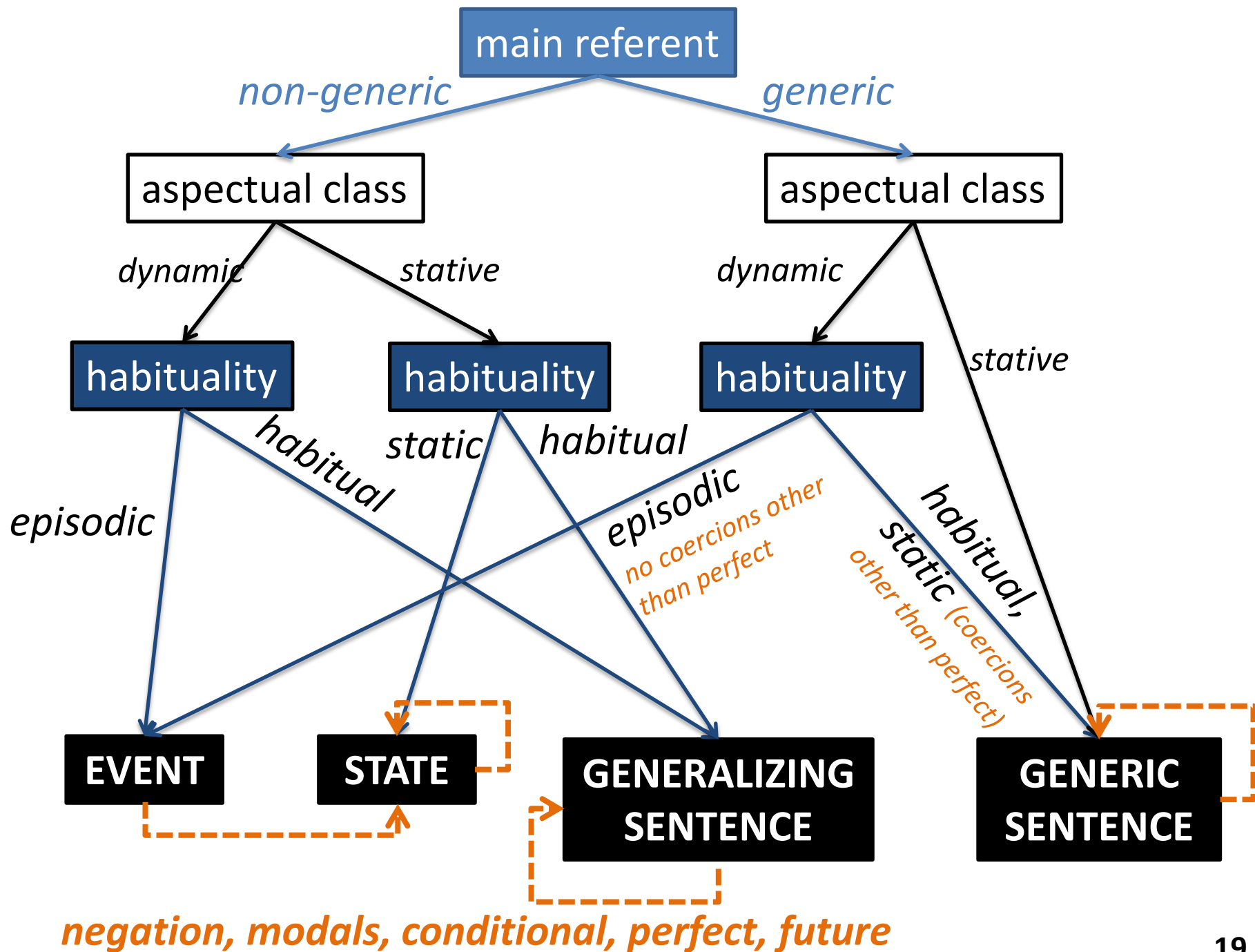
habitual: regularity

Glass breaks easily.

habitual: regularity

Mary owns four cats.

static: for STATES





SITUATION ENTITIES: ANNOTATION TOOL

USER: ANNE FRIEDRICH

HOME

LOGOUT

File: training_test_mixed.txt



8	seg_prob	... by the League of Nations after World War I, the Saarland(or simply "the Saar",
9	ST	as is frequently referred to) did not exist as a unified entity.
10	ST	Until then, some parts of it had been Prussian
11	ST	while others belonged to Bavaria.
12	EV	The inhabitants voted to rejoin Germany in a plebiscite
13	EV	held in 1935.
14	ST	From 1947 to 1956 the Saarland was a French-occupied territory(the "Saar Protectorate") separate from the rest of Germany.
15	ST	Between 1950 and 1956, Saarland was a member of the Council of Europe.
16		In 1955, in another plebiscite, the inhabitants were offered independence,
17		but voted instead for the territory to become a state of West Germany.
18		
19	seg_prob	MARS
20	ST	Mars is the fourth planet from the Sun and the second smallest planet in the Solar System.
21	ST	Named after the Roman god of war,

FEATURES

Main Referent

- ☐ *not the grammatical subject*
- ☐ non-generic ☐ expletive
- ☐ generic ☐ can't decide

Aspectual Class of main verb

- ☐ stative ☐ both
- ☐ dynamic ☐ can't decide

Habituality of main verb

- ☐ episodic ☐ static
- ☐ habitual ☐ can't decide

SEGMENTATION PROBLEMS

- ☐ no situation
- ☐ additional text
- ☐ multiple situations
- ☐ no complete situation
 - ☐ belongs to previous
 - ☐ belongs to following
 - ☐ belongs to no.:

SITUATION ENTITY

TYPES

- ☐ State
- ☐ Event
 - ☐ Report
- ☐ General Stative
 - ☐ Generalizing Sentence
 - ☐ Generic Sentence
- ☐ Abstract Entity
 - ☐ Fact
 - ☐ Proposition
 - ☐ Resemblance
- ☐ Speech Act
 - ☐ Imperative
 - ☐ Question

Comments:

Features – broader perspective

corpus data for sub-tasks studied in the NLP
community for which no large data sets are available

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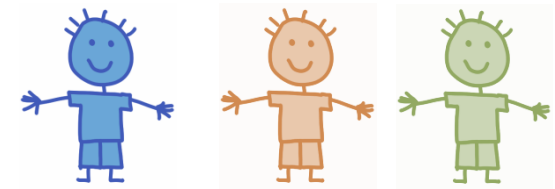
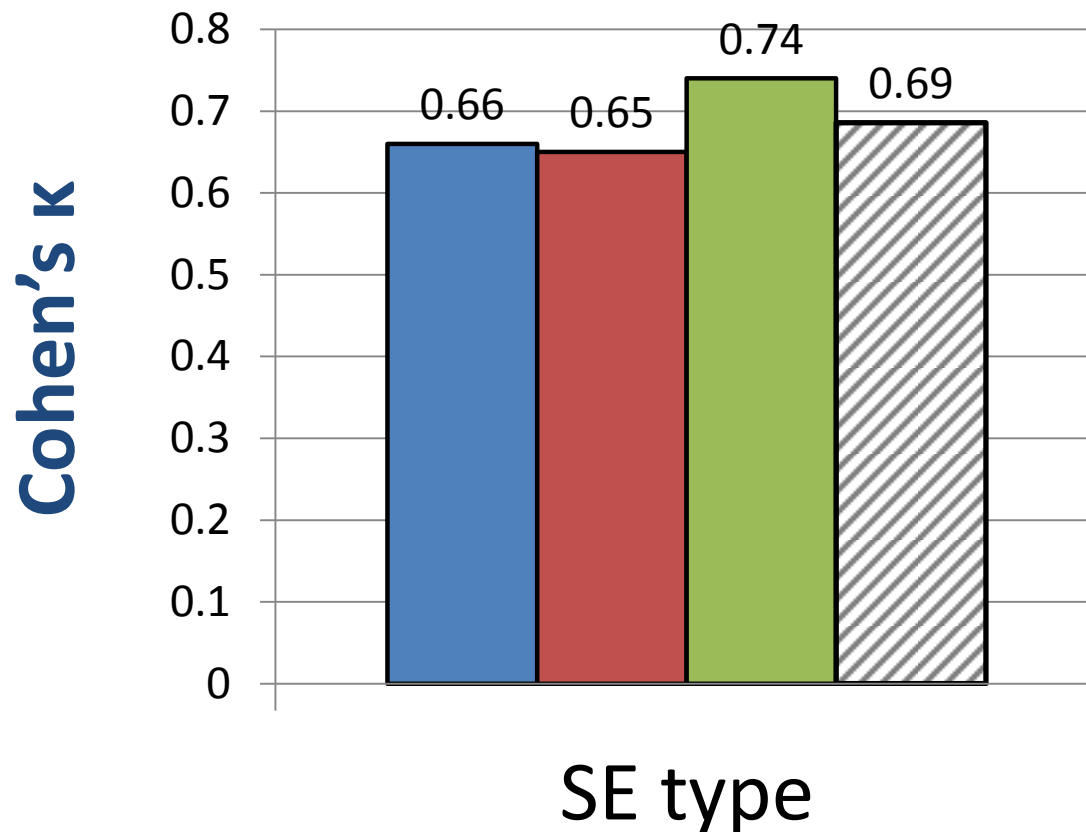
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- identifying **generic noun phrases** [Reiter & Frank 2010]
- identifying **habitual vs. episodic sentences**
[Mathew & Katz 2009]

SE types: inter-annotator agreement

labels: STATE, EVENT, GENERIC SENTENCE,
GENERALIZING SENTENCE

MASC: news (2823 situations)



pairs of annotators

■ A:B

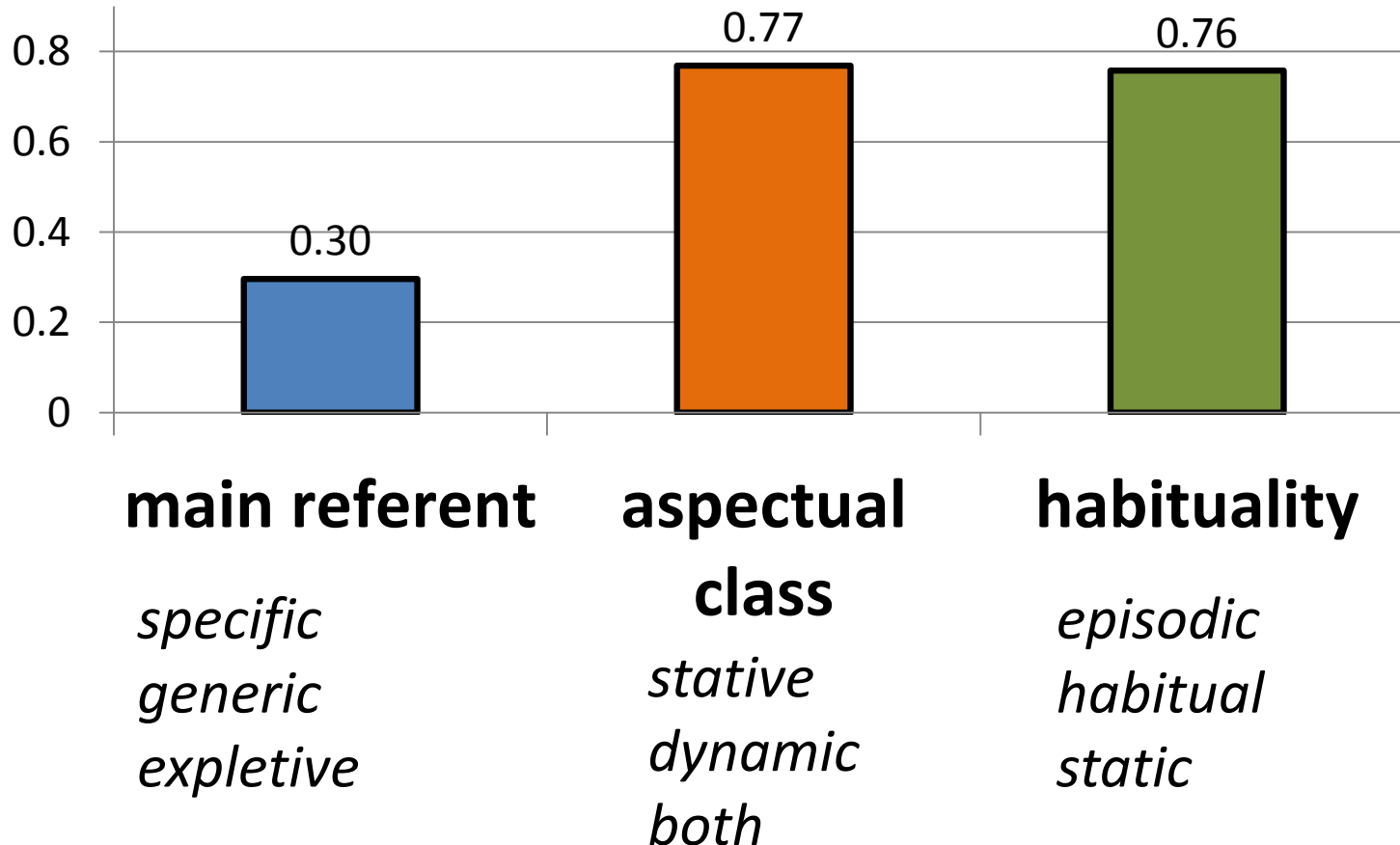
■ A:C

■ B:C

Features: inter-annotator agreement

MASC: news (2823 situations)

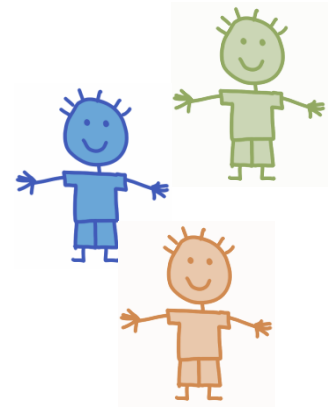
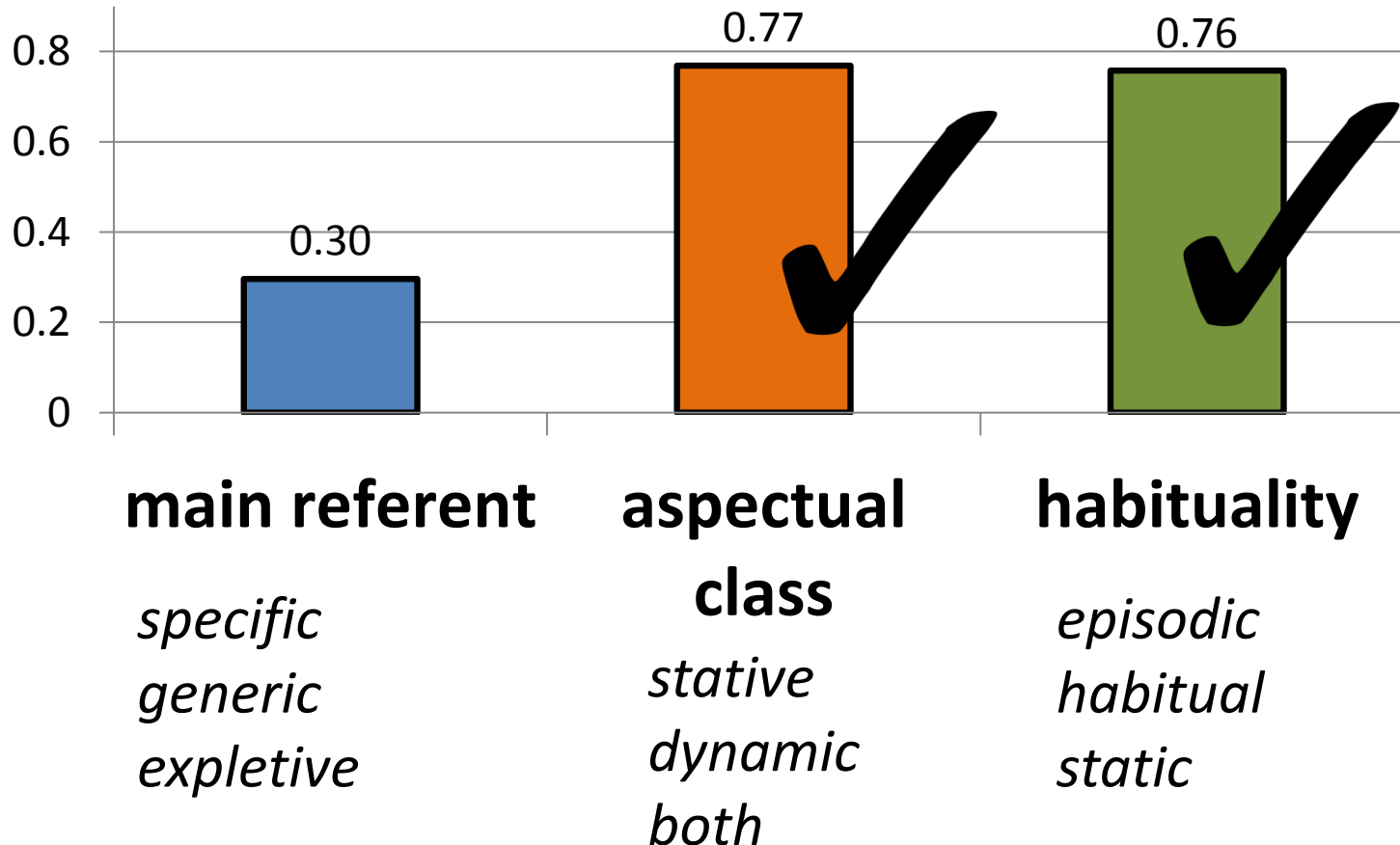
Fleiss' κ



Features: inter-annotator agreement

MASC: news (2823 situations)

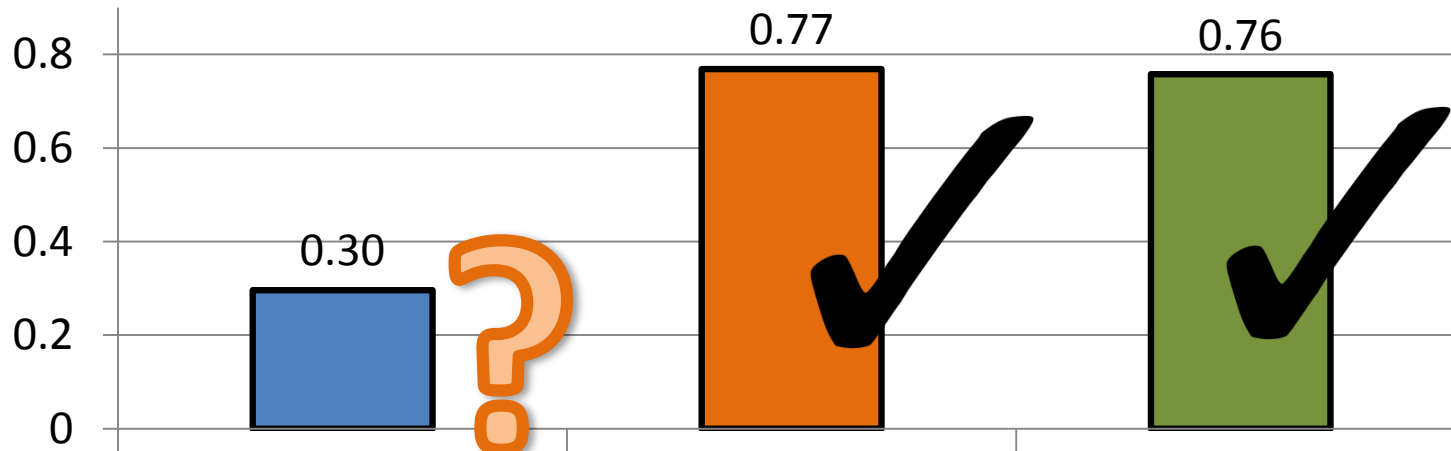
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Features: inter-annotator agreement

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Fleiss' κ



main referent

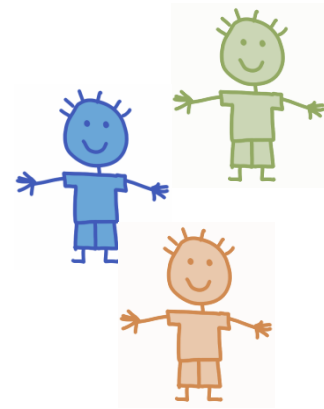
specific
generic
expletive

aspectual

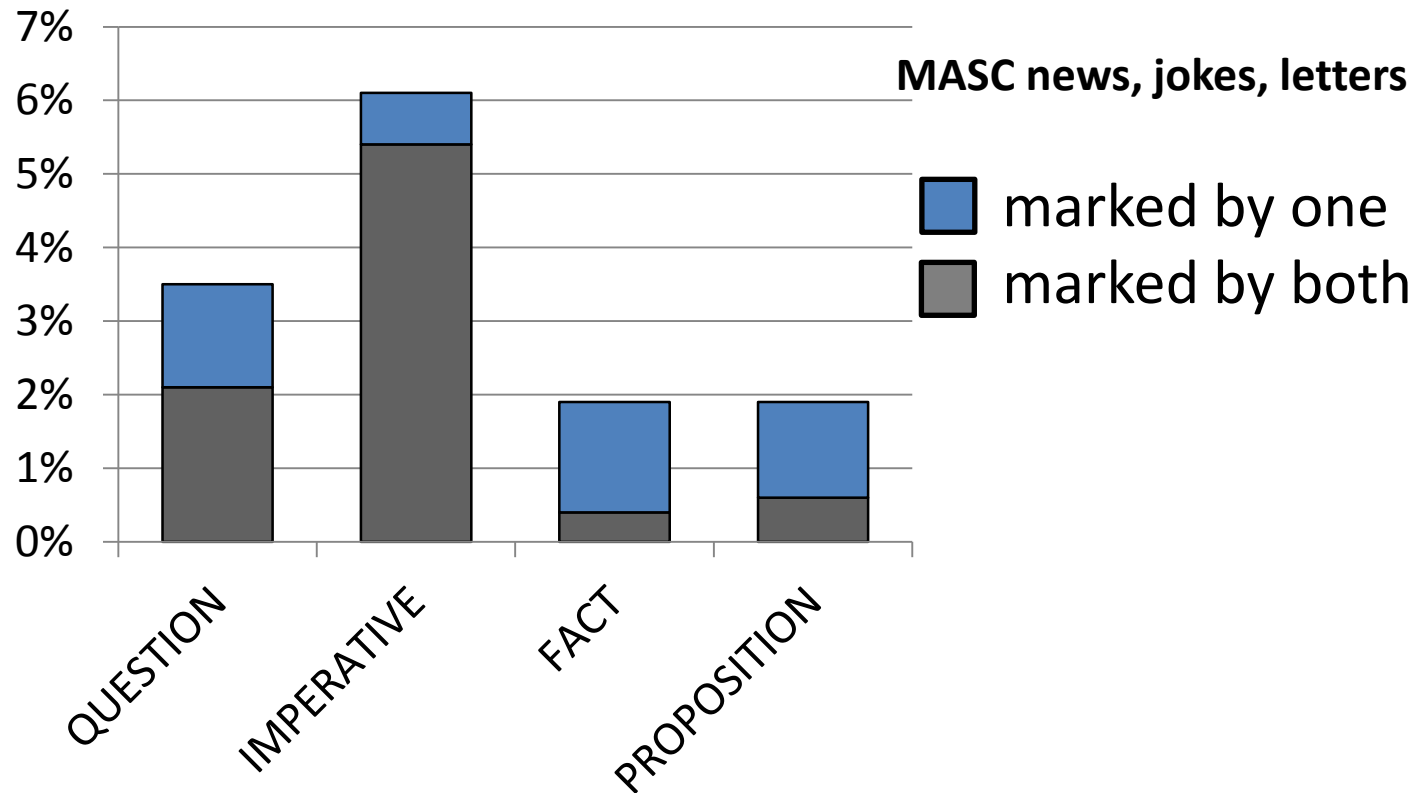
class
stative
dynamic
both

habituality

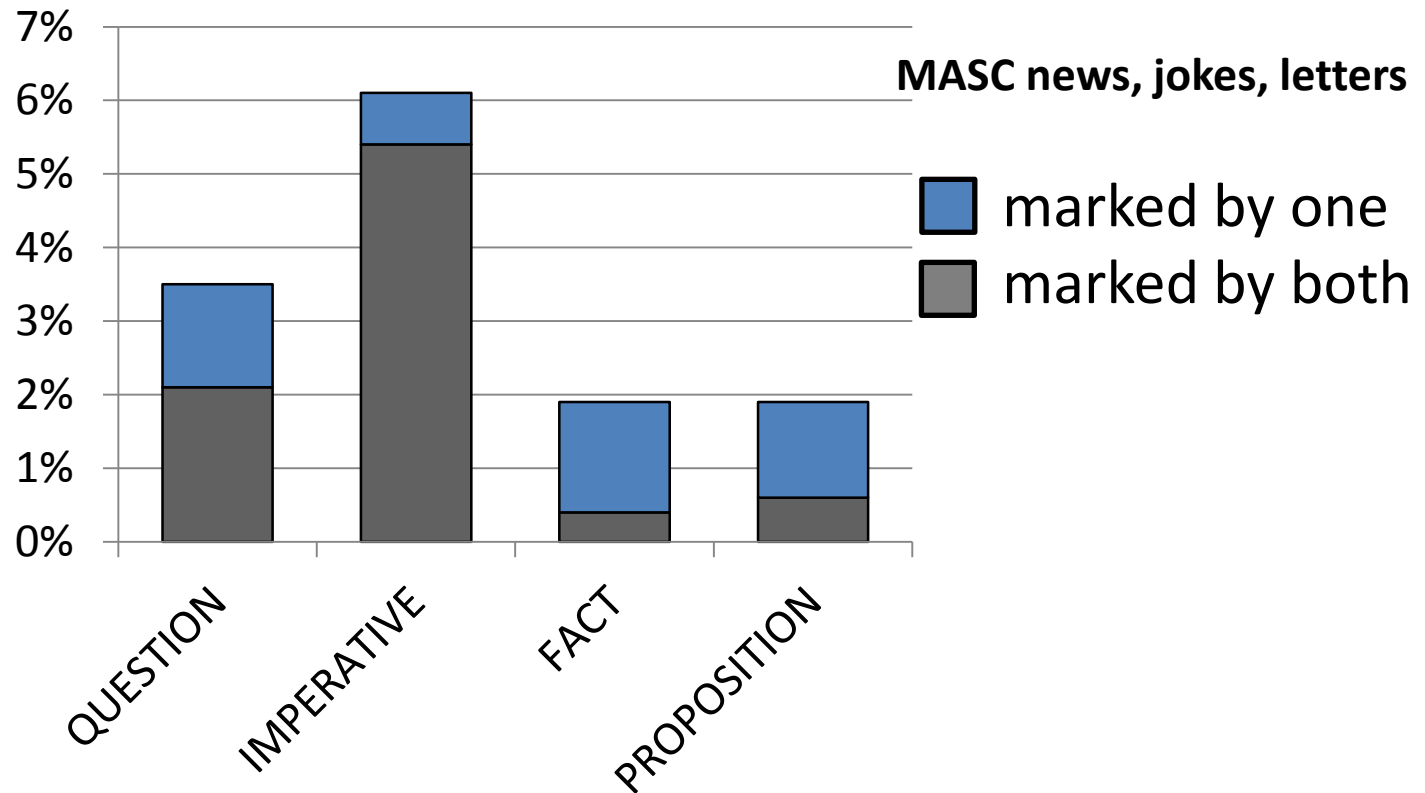
episodic
habitual
static



% of situations marked as speech acts / abstract entities:

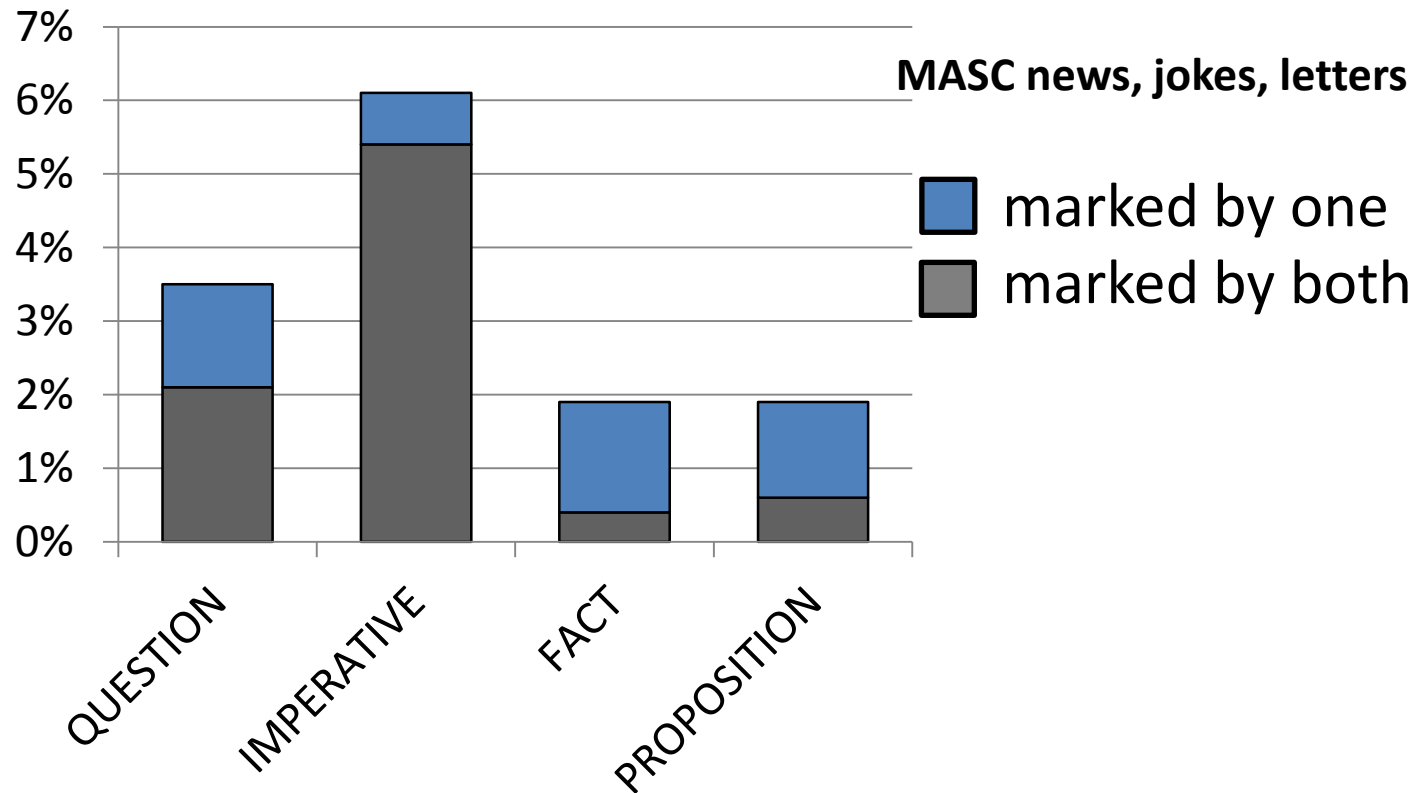


% of situations marked as speech acts / abstract entities:



indirect questions?

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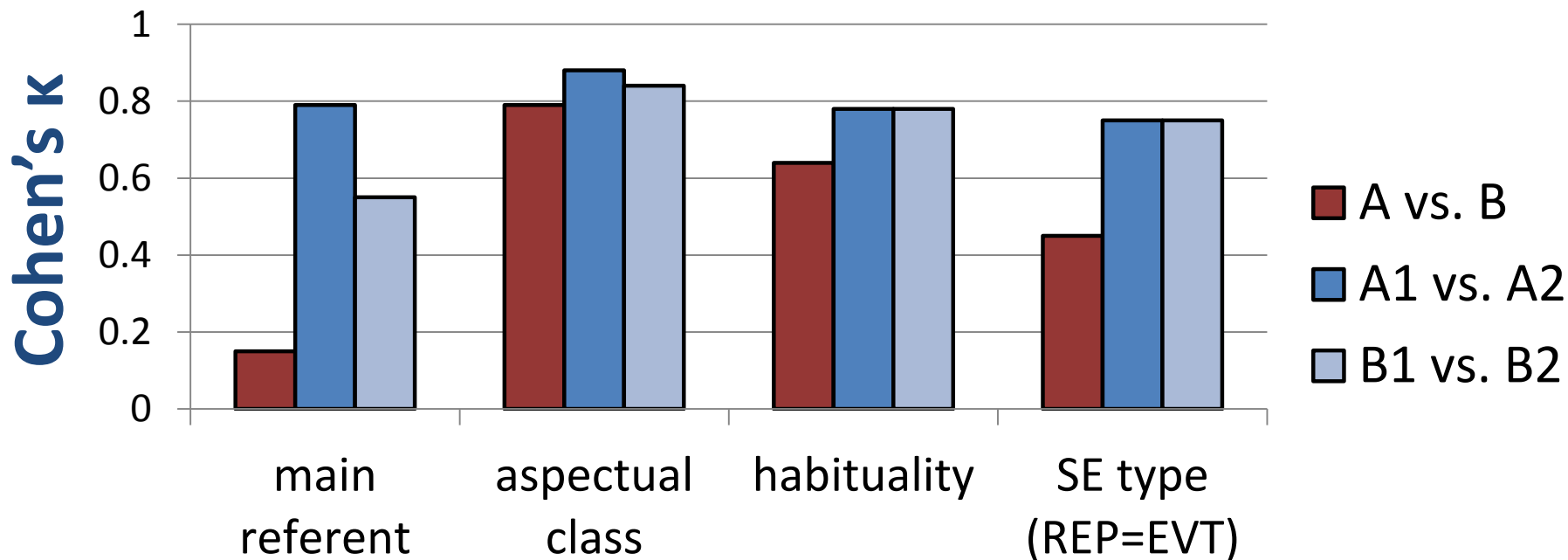
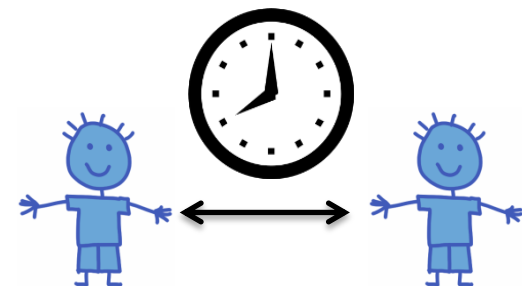


indirect questions?

no satisfying agreement yet
– lacking recall?

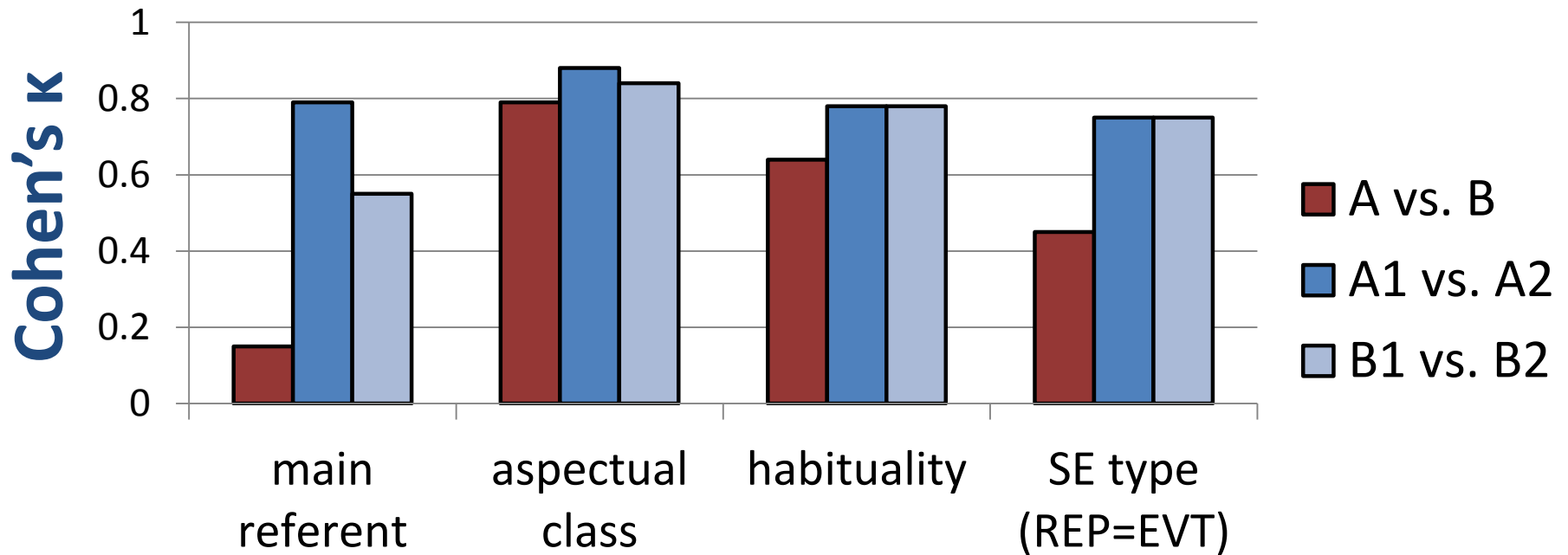
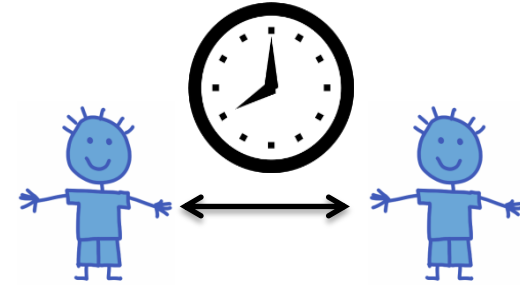
Intra-annotator consistency

11 (5 news, 5 letters, 1 jokes) documents, 600 segments
(lowest agreements on SE type)



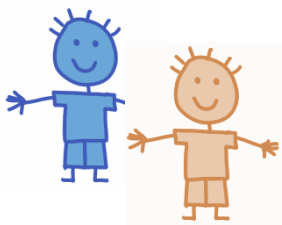
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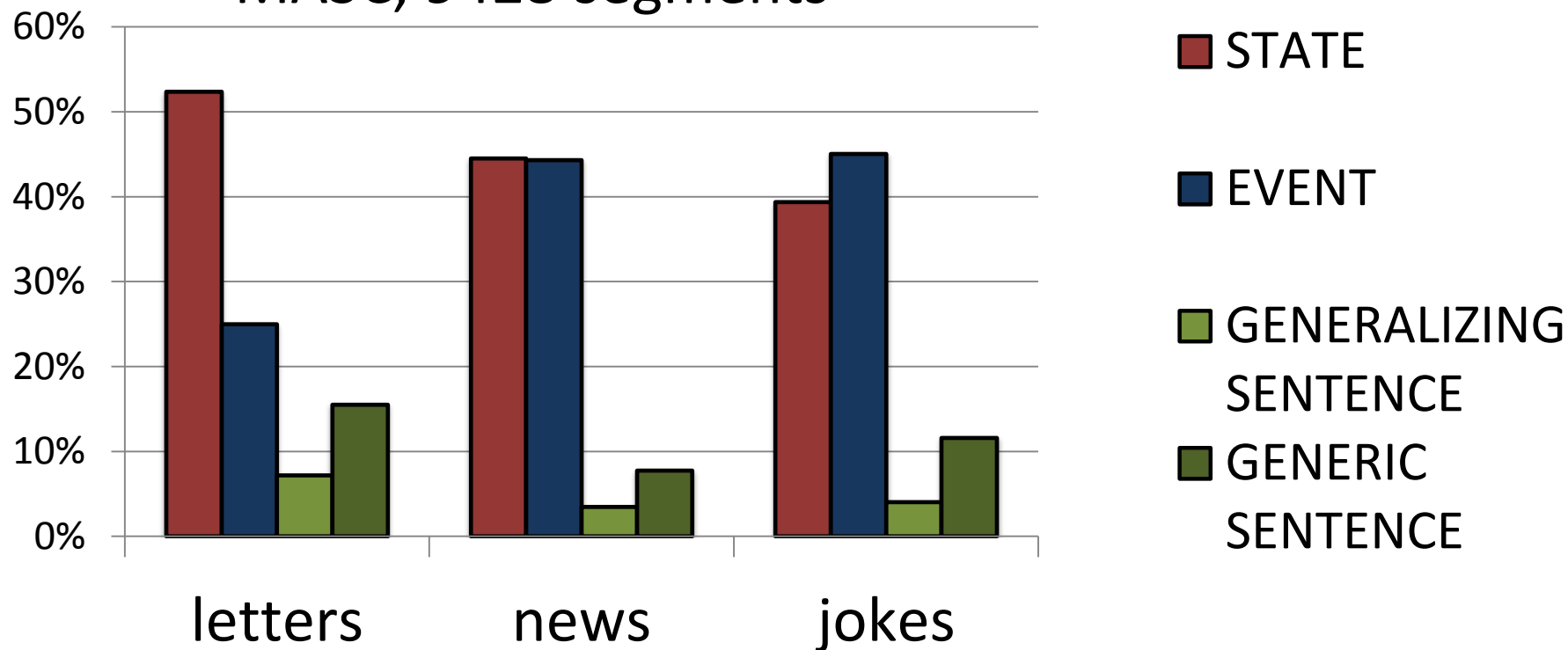
- intra-agreement > inter-agreement
 - different understanding of some cases
- annotators occasionally *do* disagree with themselves
(but: hardest part of data set, total % of noise on SE type level << 20%)

Distribution of SE types: genres

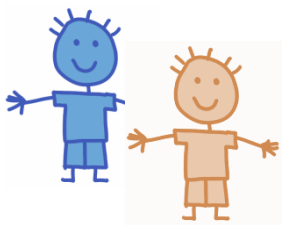


average of SE labels assigned

MASC, 9428 segments

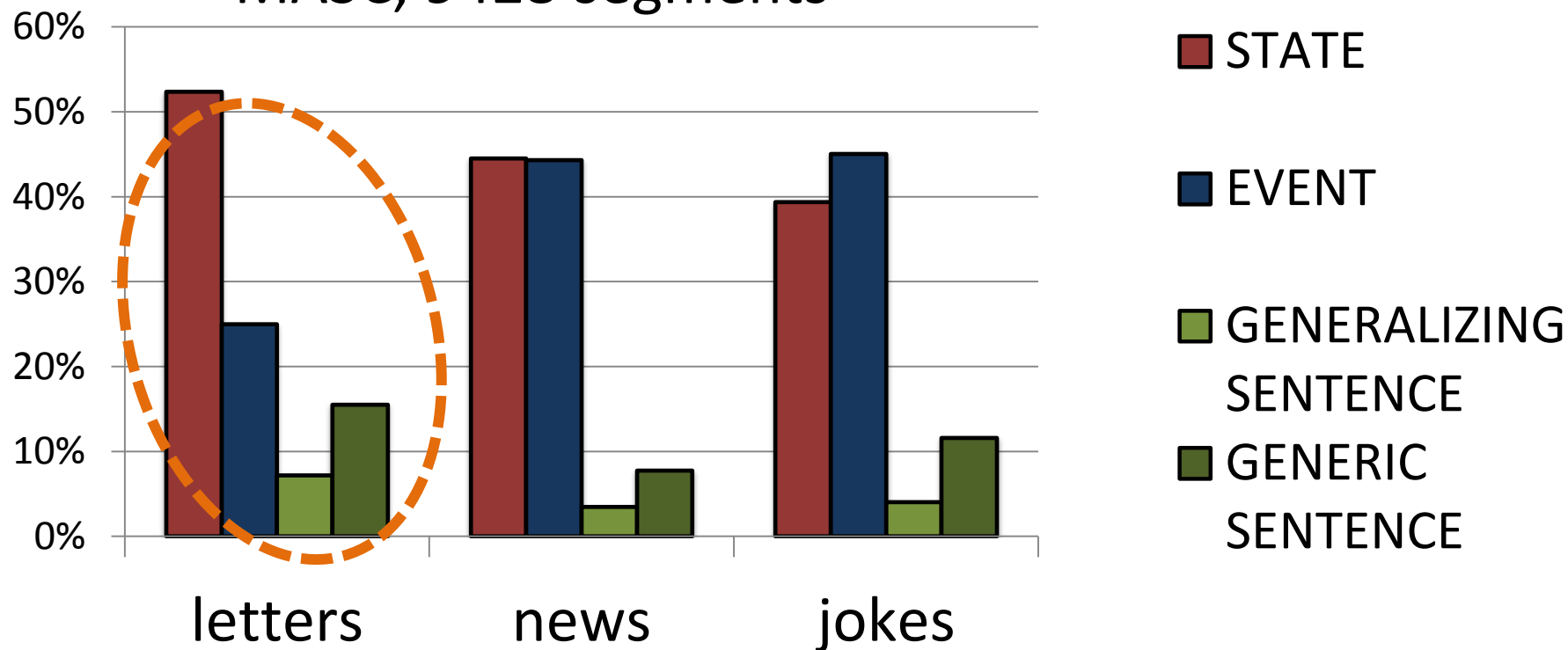


Distribution of SE types: genres



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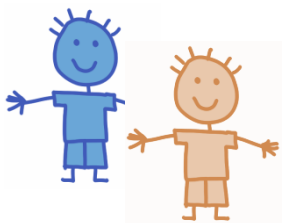
MASC, 9428 segments



➔ letters has fewer events, more **general statives**

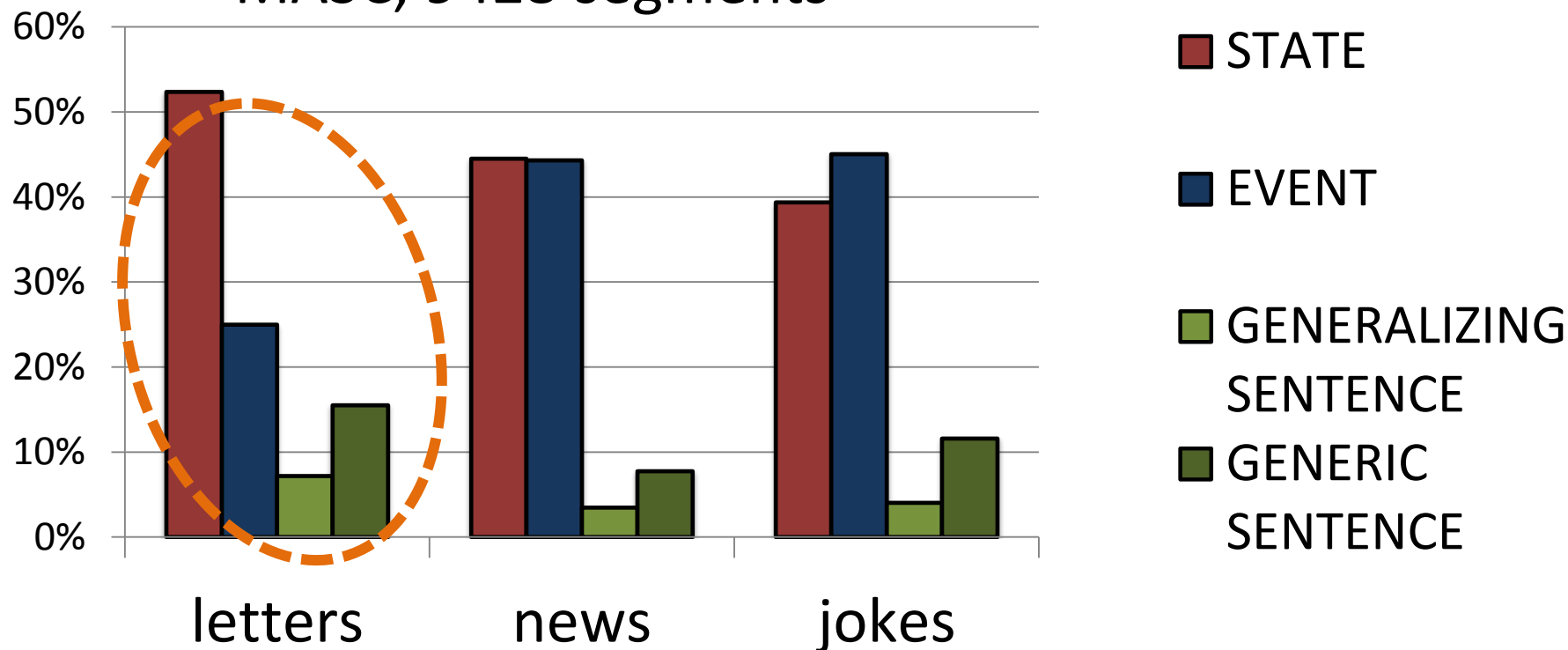
Distribution of SE types: genres

more details: [Palmer & Friedrich, 2014]



average of SE labels assigned

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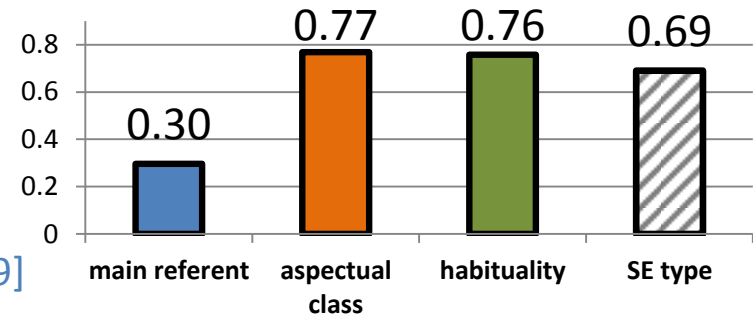
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Summary:

annotation of situation entity types

- Annotation guidelines for situation entity types:
 - substantial agreement achieved for SE type, aspectual class & habituality
 - part of disagreements: hard cases
→ leverage for training

[Plank et al. 2014, Beigman Klebanov & Beigman 2009]

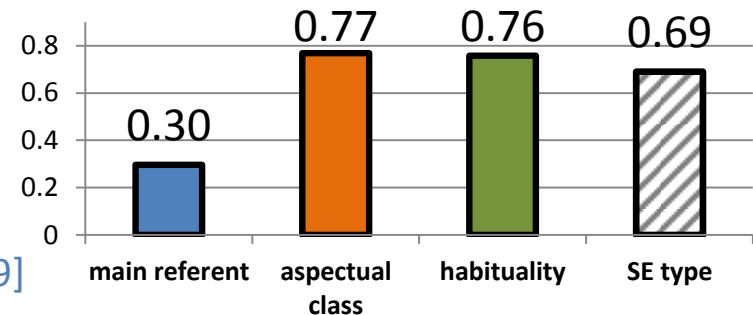


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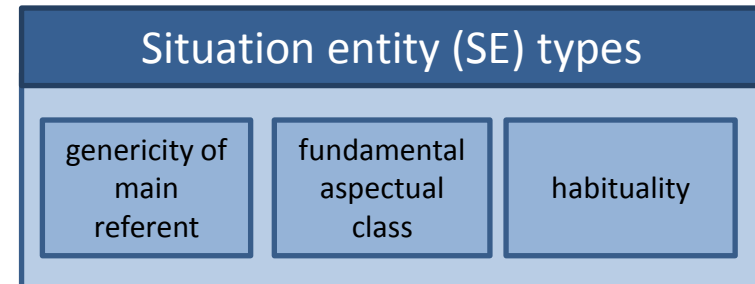
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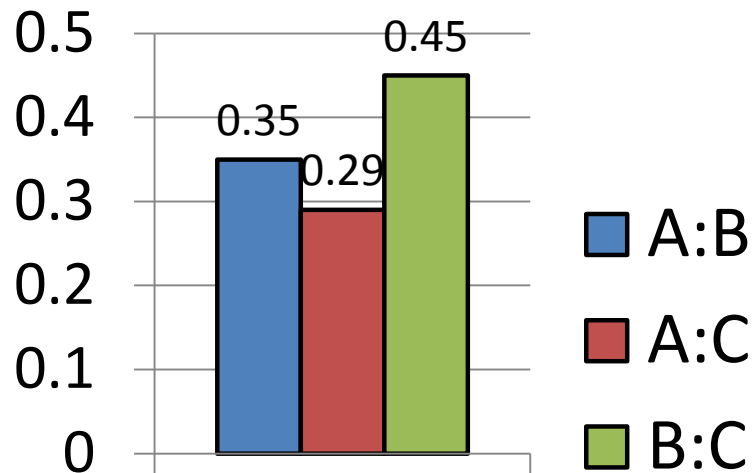


- Feature-based approach
 - helps annotators during annotation
 - analysis of disagreements
 - identify problems in guidelines
→ follow-up study on genericity



Feature: genericity of main referent (inter-annotator agreement)

Cohen's κ



**main
referent**

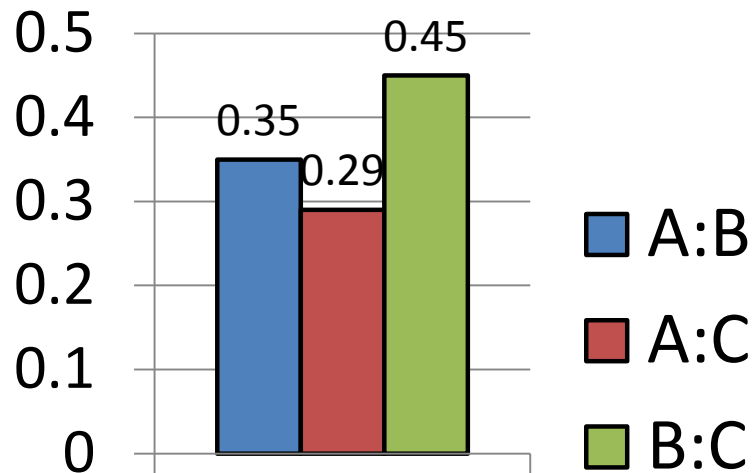
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specific

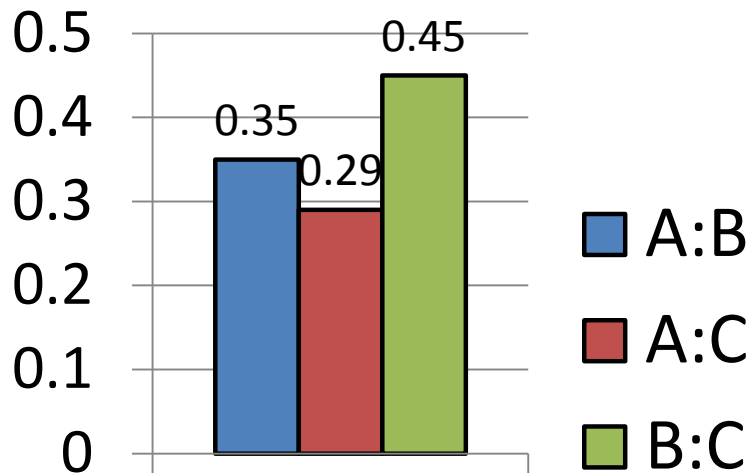
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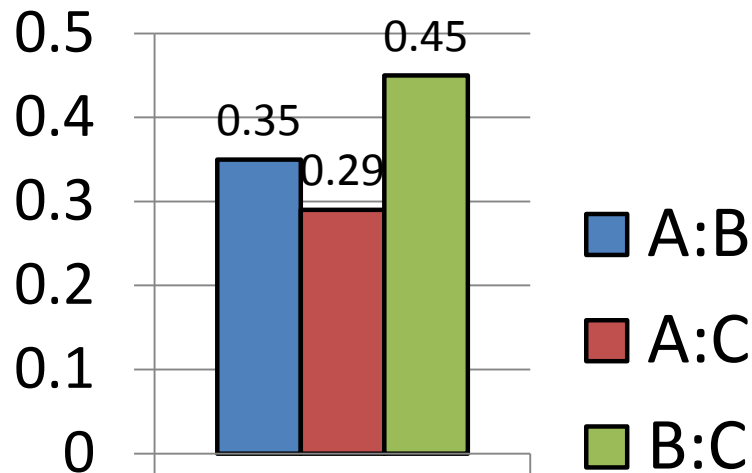
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- **clarity** of annotation guidelines?

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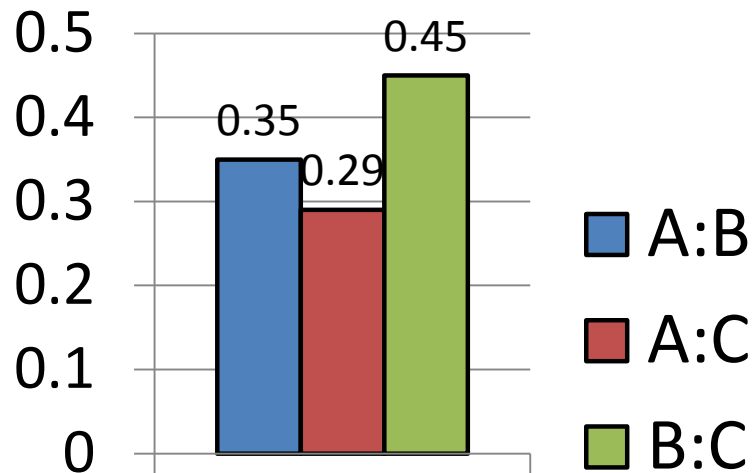
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- **clarity** of annotation guidelines?
- ***sparsity*** of label *generic*:
 - B&C ($\kappa = 0.45$)
 - 2358 non-generic
 - 122 generic by one
 - 43 generic by both

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- **clarity** of annotation guidelines?
- ***sparsity*** of label *generic*:
 - B&C ($\kappa = 0.45$)
 - 2358 non-generic
 - 122 generic by one
 - 43 generic by both
- ***ambiguity / underspecification***
 - ~ 30% of disagreements (estimate based on small qualitative analysis)
 - every kid in New York*
 - “you” in letters*

Generics follow-up study

address the issue of *clarity*:
compared definition to existing theories [Carlson & Pelletier 1995]
& corpora (ACE 2005),
clarified definition in manual, added examples.

Generics follow-up study

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compared definition to existing theories [Carlson & Pelletier 1995]

& corpora (ACE 2005),

clarified definition in manual, added examples.

Generic noun phrases (theory applied to subjects):

(compare to Krifka et al. 1995: “The Generic Book”)

kind-referring: *The lion disappeared from Asia.*

nonspecific, referring to arbitrary member of kind:

A lion roars when it smells food.

Generics follow-up study

- address the issue of *sparsity*: enrich corpus with documents where we expect a higher proportion of general statives

Generics follow-up study

- address the issue of ***sparsity***: enrich corpus with documents where we expect a higher proportion of general statives
- **Wikipedia documents**: ≈ 6100 situations, $\approx 50\%$ marked generic

category
animals
games
gangs
history
sports
tribes

The blobfish is a deep sea fish of the family...

Blobfish are typically shorter than 30cm.

*American football is a sport
played by two teams of eleven players.*

The offense attempts to advance an oval ball ...

*Five cards are dealt from a standard 52-card deck.
The player with the most piles wins.*

*The Bari tribe feels the effects as a whole.
The Bari trade ...*

Generics follow-up study

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inductive

[Carlson 1995]

American football is a sport

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The offense attempts to advance an oval ball ...

rules and regulations

Five cards are dealt from a standard 52-card deck.

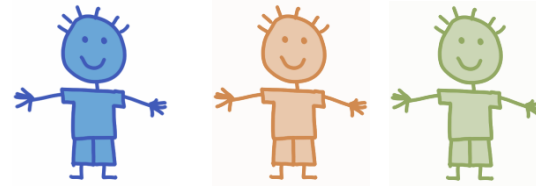
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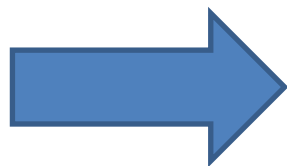
Wikipedia documents: agreement

- WikiGen corpus: 49 documents (≈ 6100 situations)
- agreement study: 14 documents (≈ 1800 situations),
3 annotators



Fleiss' K

main referent	aspectual class	habituality	SE type
0.64	0.66	0.63	0.67



substantial agreement

Generics follow-up study: lesson learned

- 1) Descriptions in **manual** were clarified, added more examples → third newly hired annotator learned scheme almost exclusively from manual.

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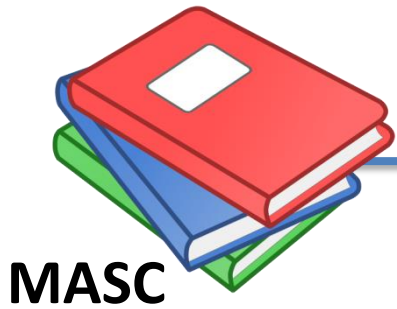
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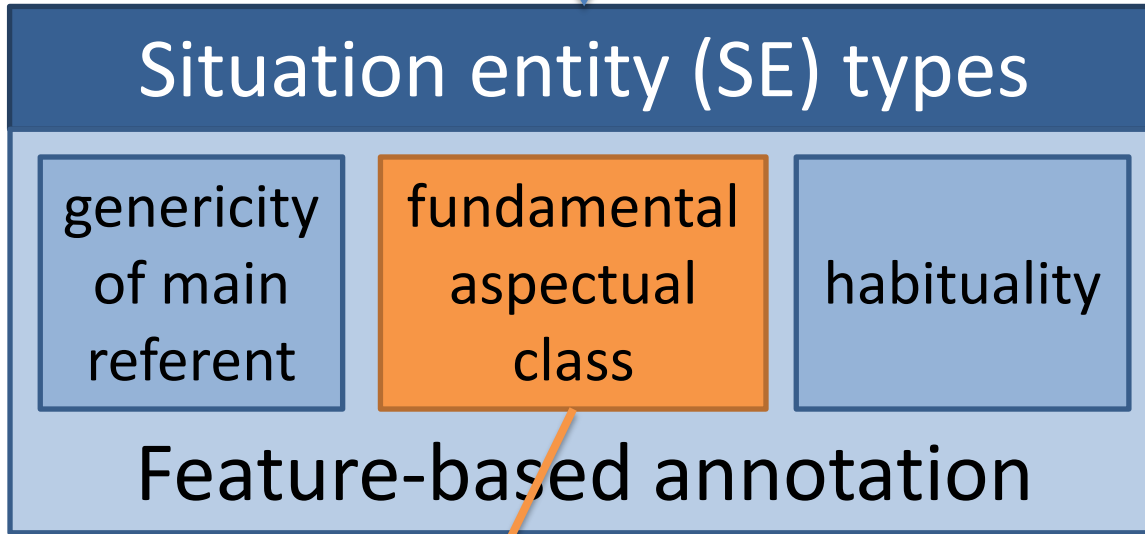
substantial agreement

TODO: build computational model for detecting genericity of clauses

Overview

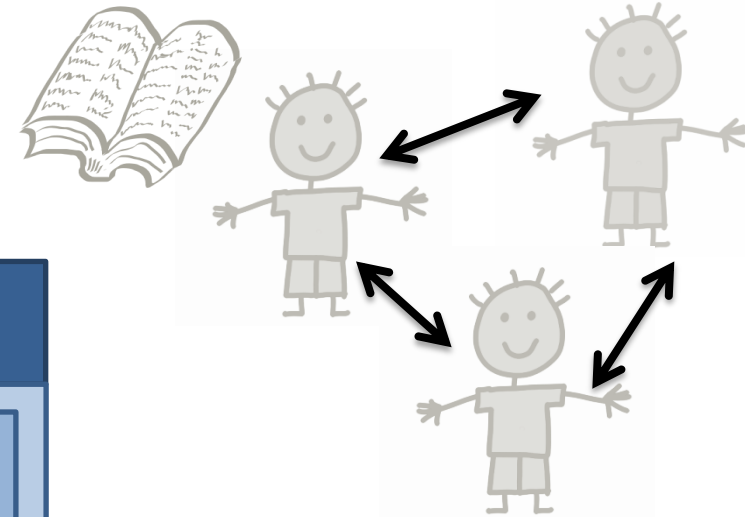


(automatic) segmentation

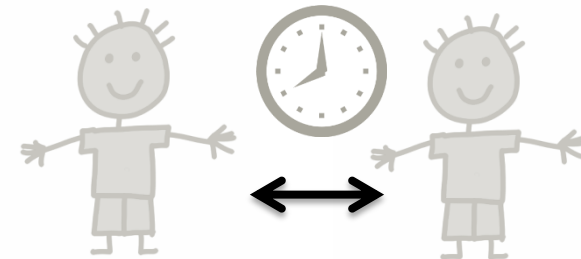


2) automatic classification

1) Corpus annotation



inter-annotator
agreement



intra-annotator
consistency

Automatic prediction of aspectual class of verbs in context

[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**

Linguistic background

Vendler (1957):

time schemata of **verbs**

**lexical aspect /
aktionsart**

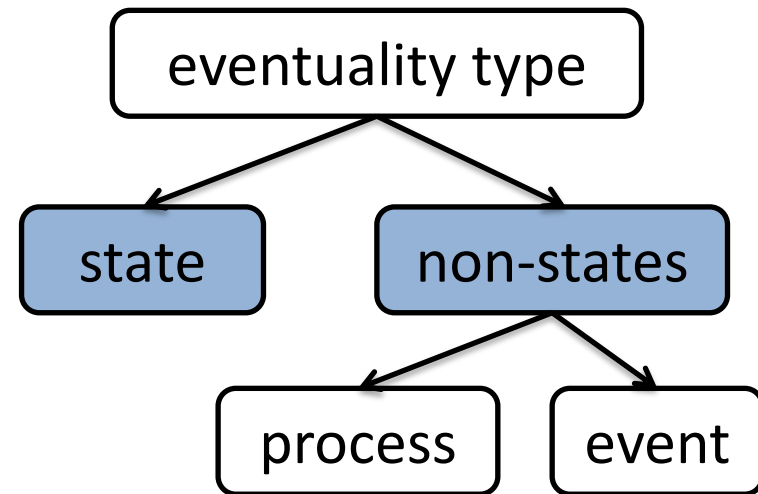
states	<i>love, own</i>	stative
activities	<i>run</i>	dynamic
accomplishments	<i>write a letter</i>	
achievements	<i>realize</i>	

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Bach (1986):
time schemata of
sentences



Task: predicting fundamental aspectual class

- a function of the main verb and a select group of arguments (may differ per verb)
- Siegel & McKeown (2000)

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

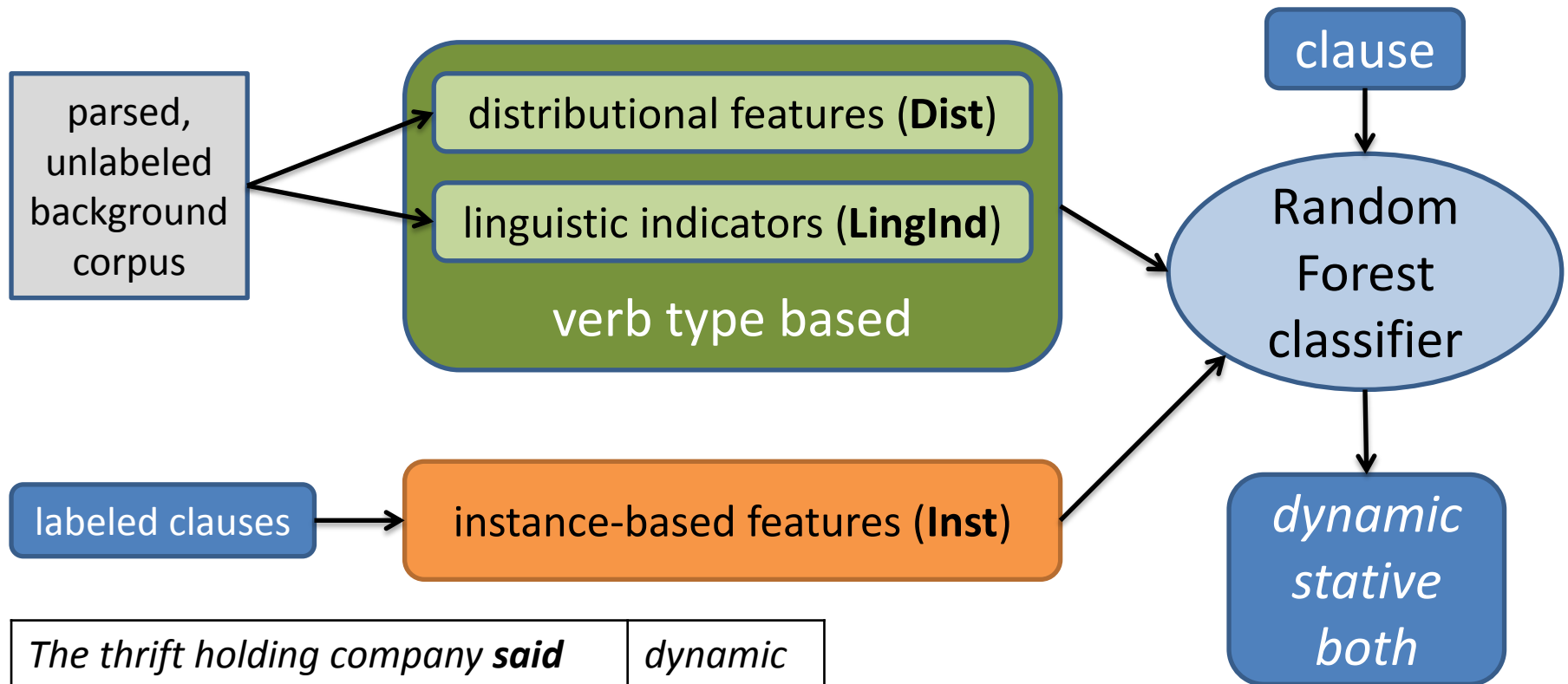
Task: predicting fundamental aspectual class

- a function of the main verb and a select group of arguments (may differ per verb)
- Siegel & McKeown (2000)
 - evaluation **type-based**
 - our work: **instance-based**

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Method: Overview

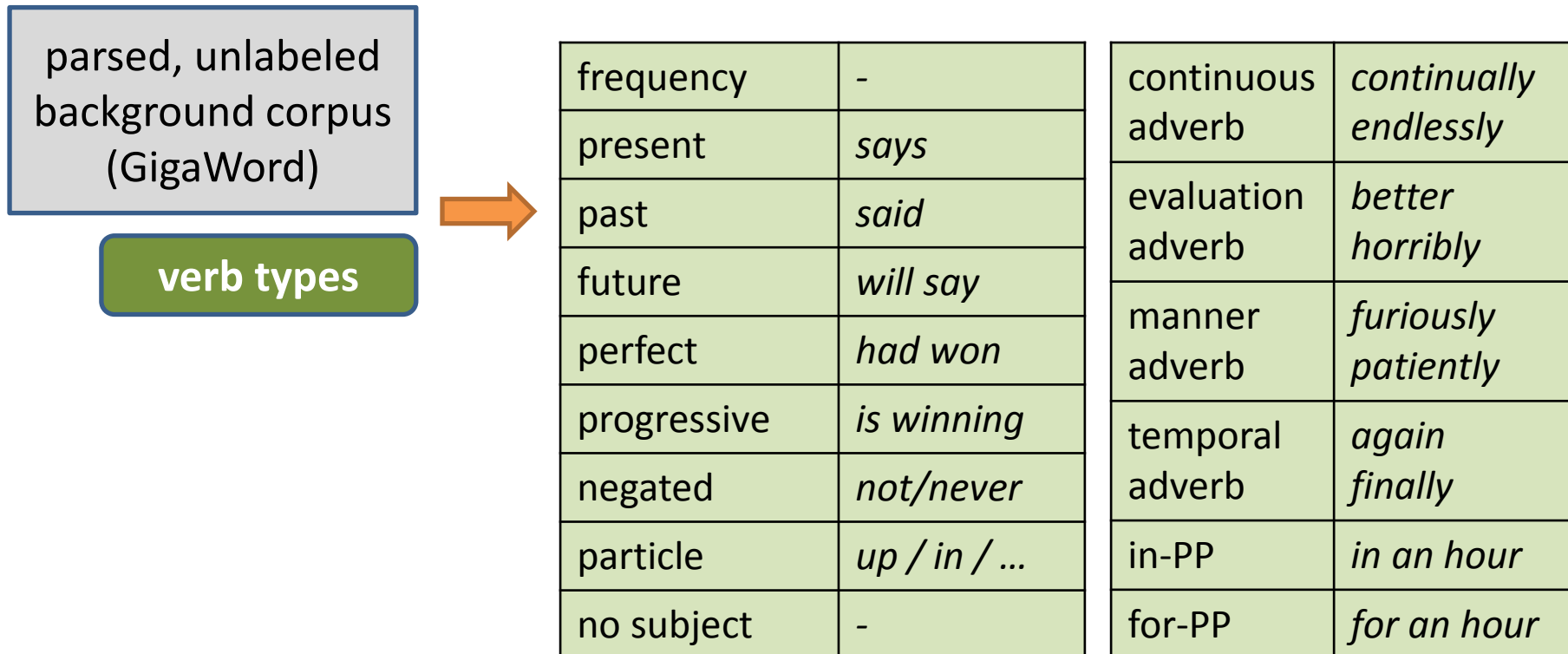
- supervised three-way classification setting



<i>The thrift holding company said</i>	<i>dynamic</i>
<i>it expects to obtain approval</i>	<i>stative</i>
<i>and recognizes the danger.</i>	<i>both</i>

Linguistic Indicators

- co-occurrence of **verb types** with certain linguistic features (Siegel & McKeown 2000)



Linguistic Indicators


- co-occurrence of **verb types** with certain linguistic features (Siegel & McKeown 2000)

parsed, unlabeled
background corpus
(GigaWord)

verb types

verb type: **fill**
feature: **temporal-adverb**
value: **0.0085**

0.85% of the occurrences
of fill are modified by one
of the temporal adverbs.

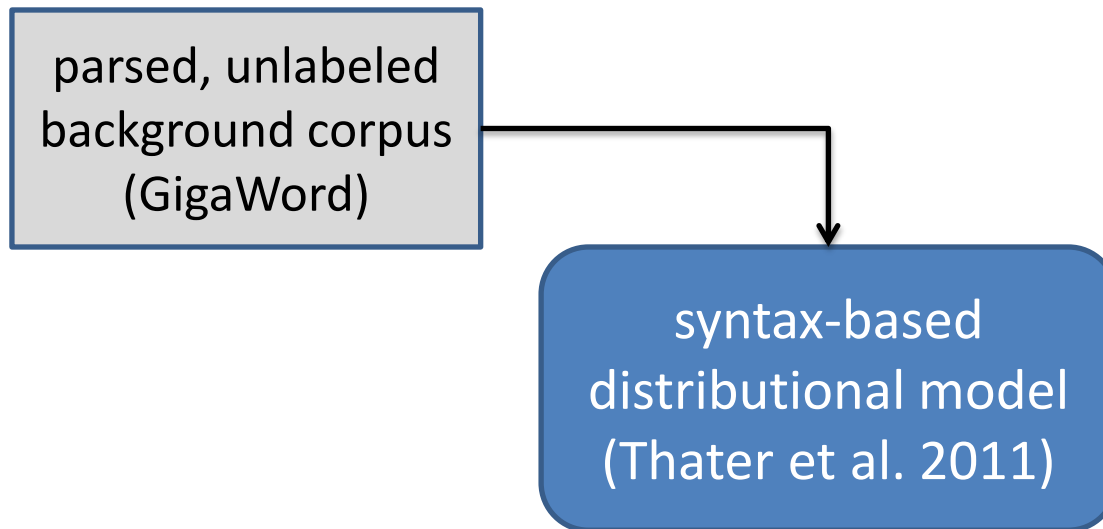


frequency	-
present	<i>says</i>
past	<i>said</i>
future	<i>will say</i>
perfect	<i>had won</i>
progressive	<i>is winning</i>
negated	<i>not/never</i>
particle	<i>up / in / ...</i>
no subject	-

continuous adverb	<i>continually</i> <i>endlessly</i>
evaluation adverb	<i>better</i> <i>horribly</i>
manner adverb	<i>furiously</i> <i>patiently</i>
temporal adverb	<i>again</i> <i>finally</i>
in-PP	<i>in an hour</i>
for-PP	<i>for an hour</i>

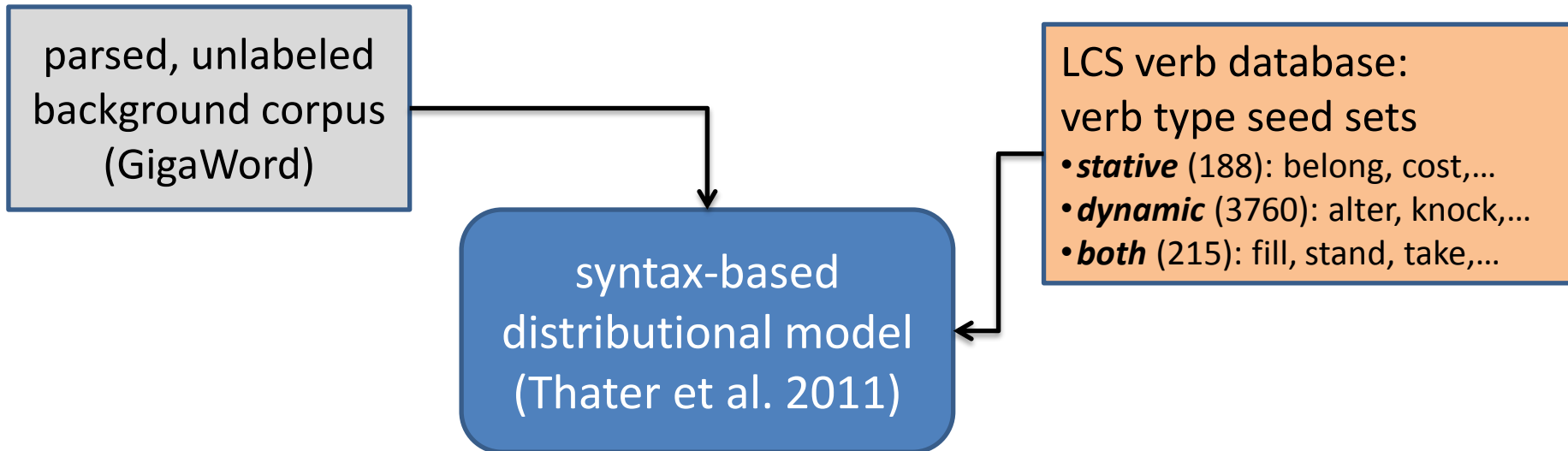
Distributional features

- average similarities with verbs in seed sets



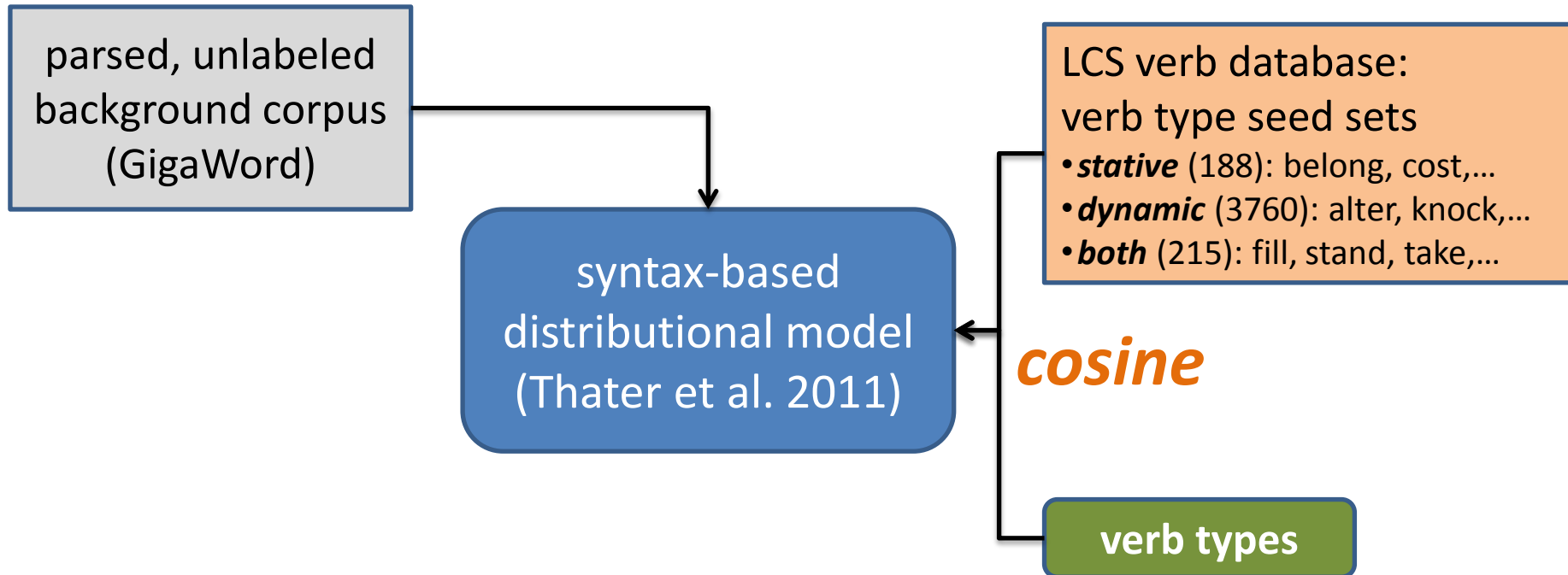
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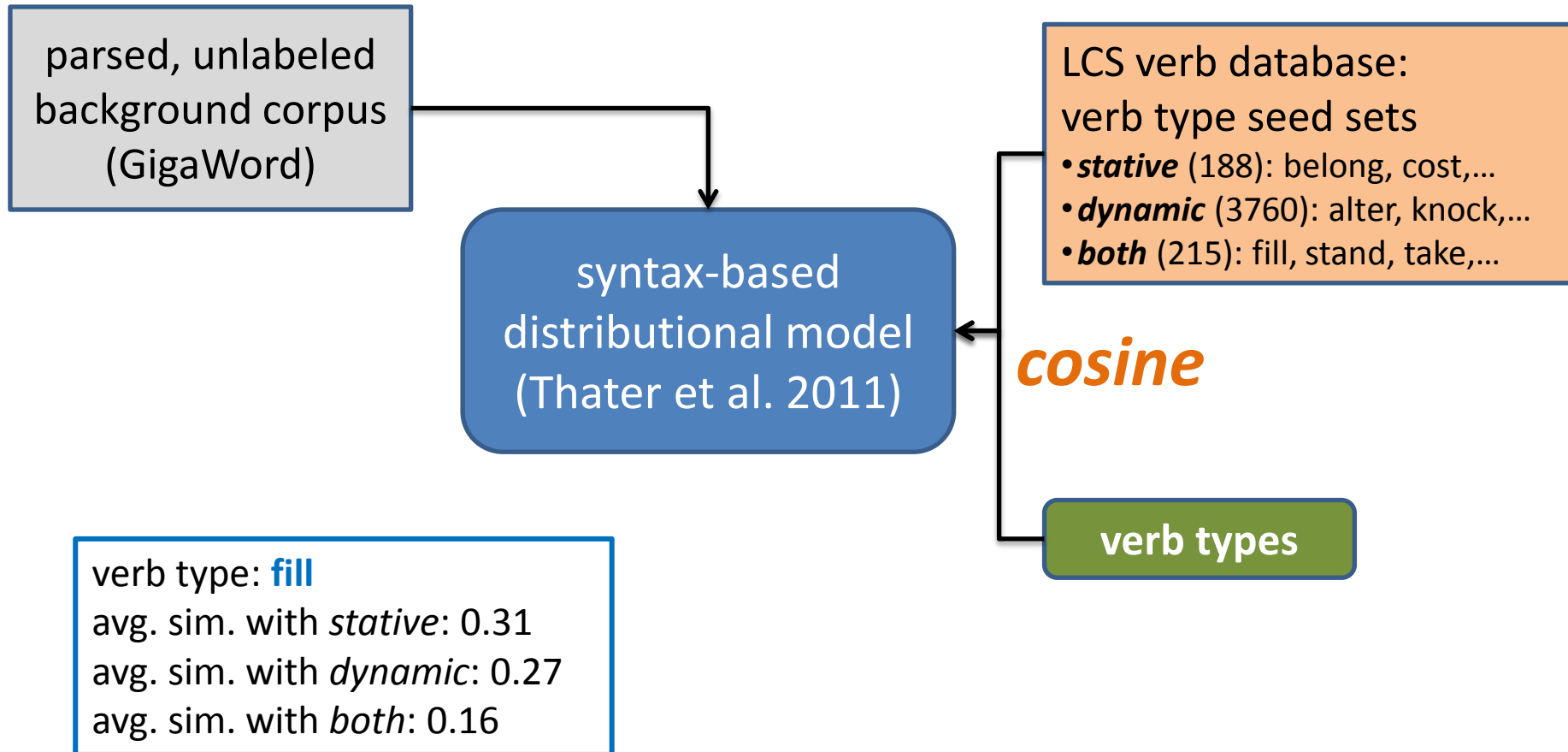
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Instance-based features

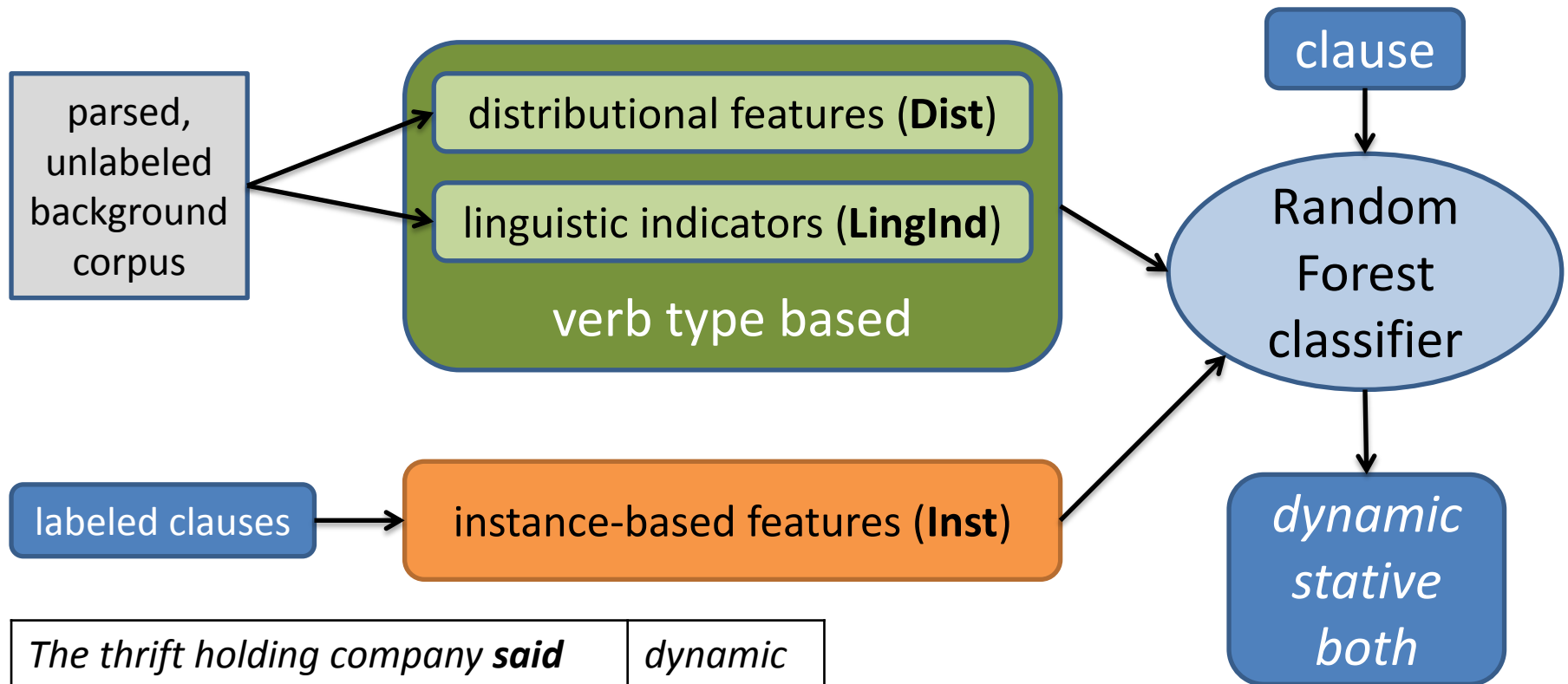
- verb-centric syntactic-semantic features

*A little girl had just **finished**
her first week of school.*

tense :past	progressive :false
pos :VBD	dobj :noun.time
perfect :true	particle :none
voice :active	subj :noun.person

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- supervised three-way classification setting



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Experiments 1&2: SEEN vs. UNSEEN verbs

Asp-MASC: 6161 clauses (complete texts) excluding be/have,
2 annotators, $\kappa = 0.7$, 10-fold cross validation

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SEEN verbs:

labeled training data
available

Type-based features

→ same accuracy (**84%**)
as only using Lemma
(= *memorizing most
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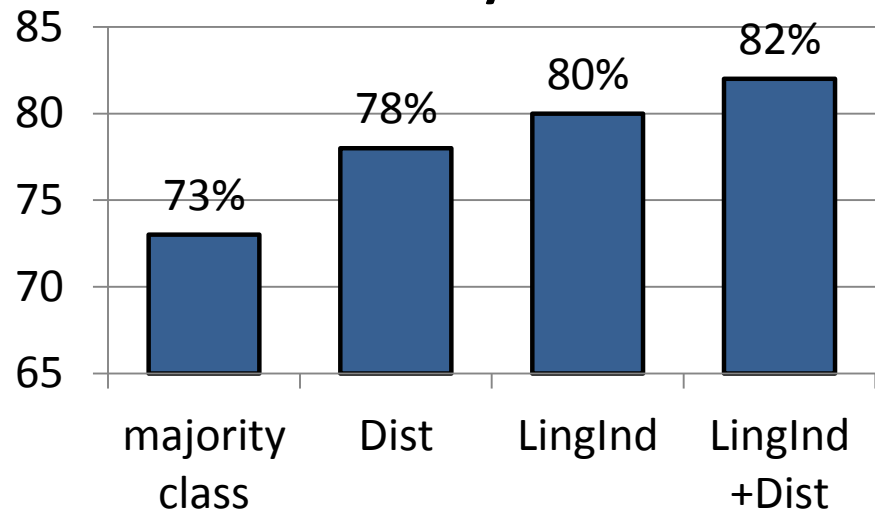
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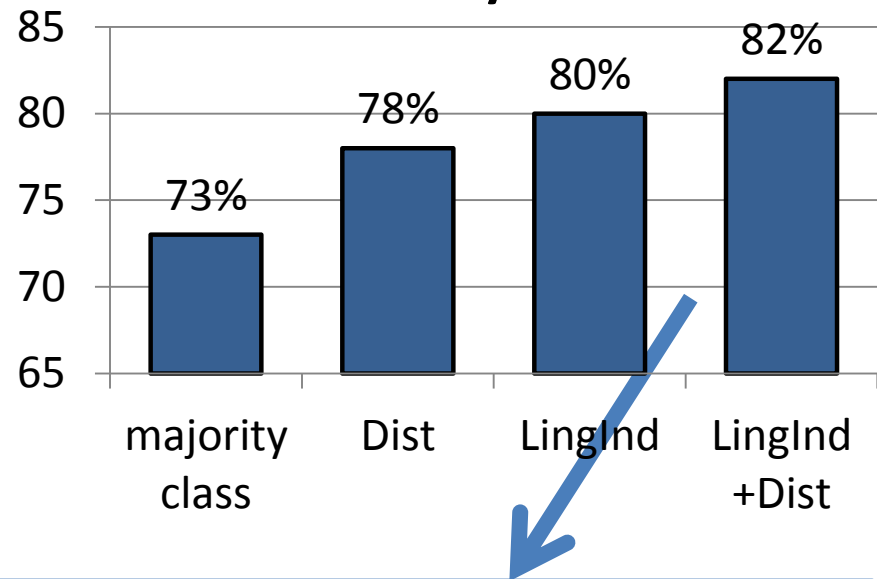
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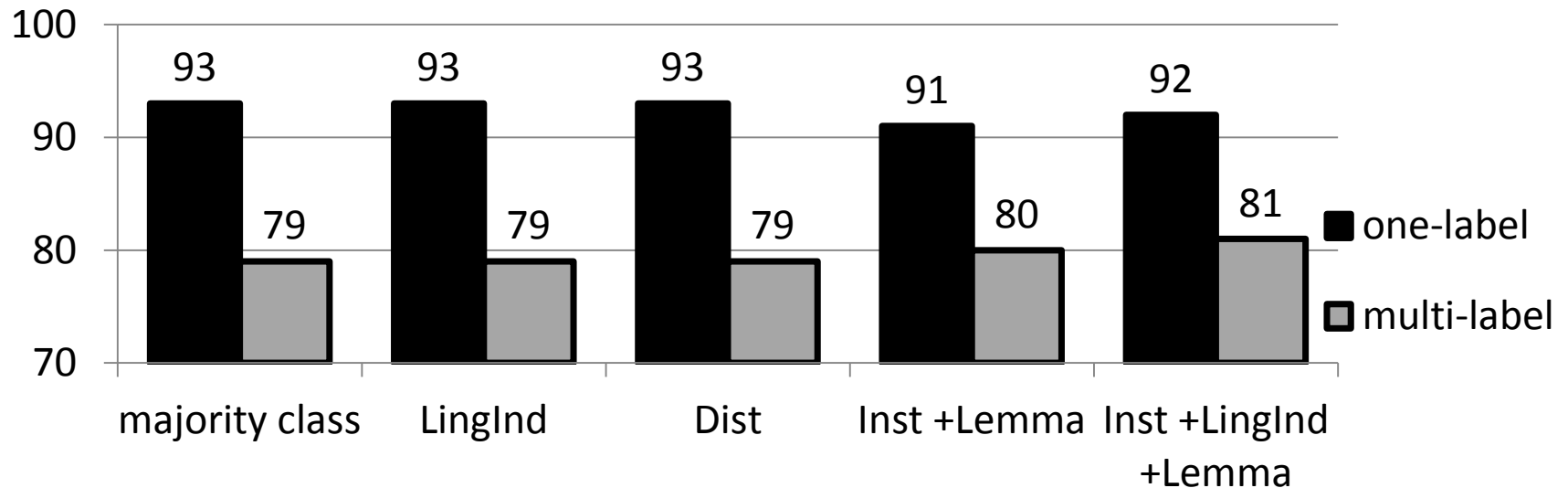


Type-based features generalize across verb types.

Experiment 3:

ONE-LABEL vs. MULTI-LABEL verbs

accuracy in %



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accuracy in %



Experiment 3: ONE-LABEL vs. MULTI-LABEL verbs

accuracy in %



same performance

★ significantly better than majority class

Instance-based features are essential
for classifying ambiguous verbs.

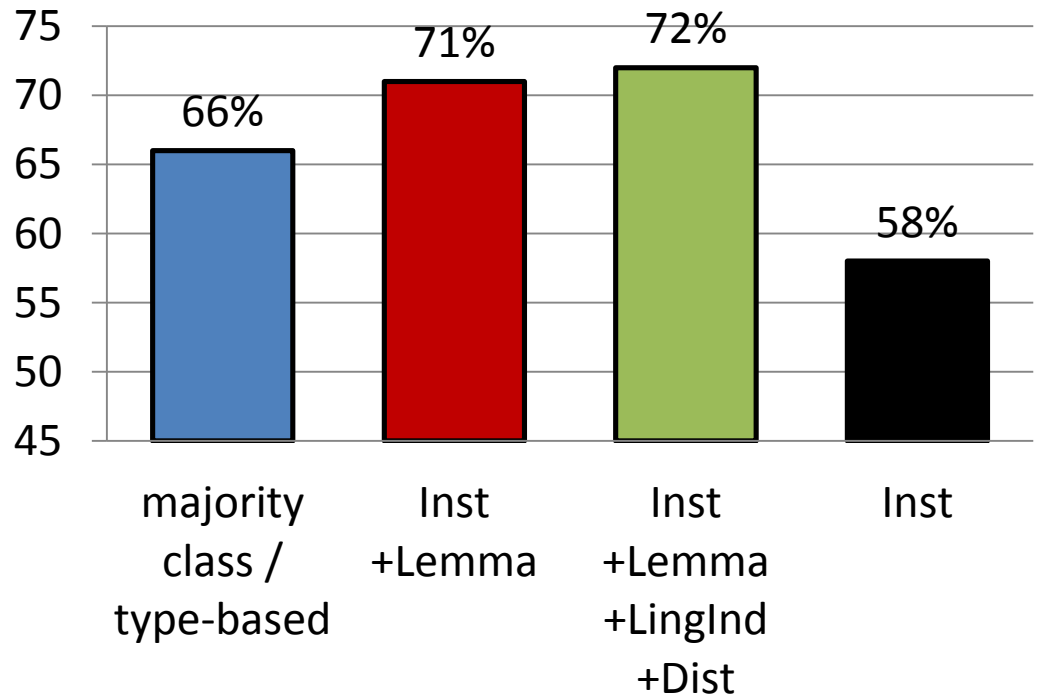
Experiment 4: INSTANCE-BASED classification

Asp-Ambig:

- 2667 sentences for 20 frequent ambiguous verbs (from Brown)
- 2 annotators, $\kappa = 0.6$

Experiment 4: INSTANCE-BASED classification

Asp-Ambig: micro-average accuracy

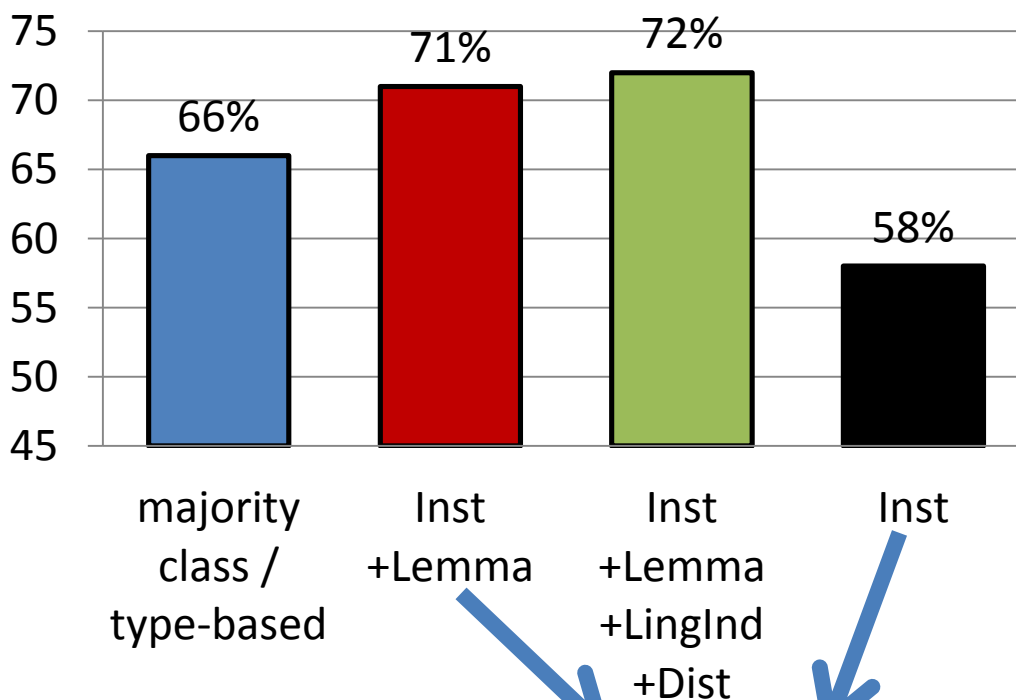


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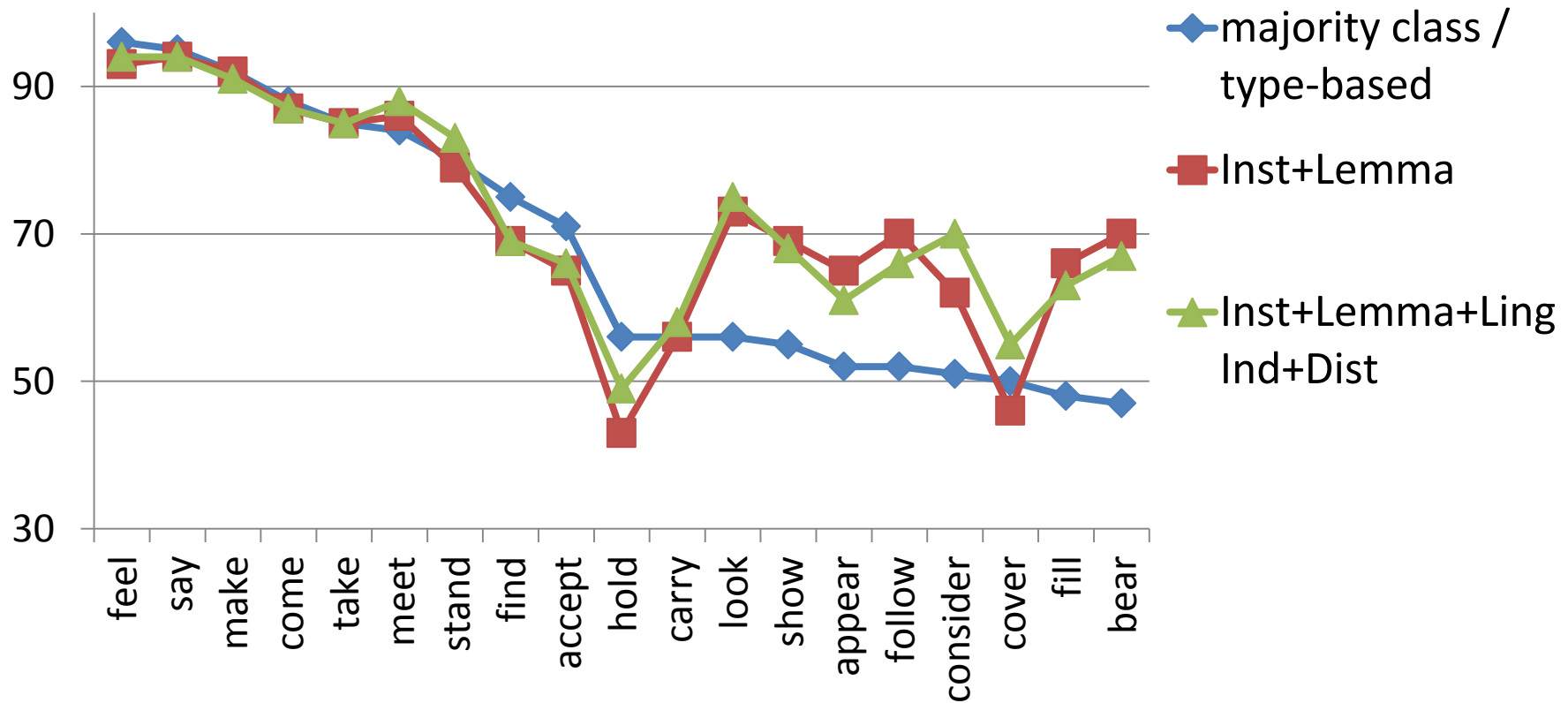


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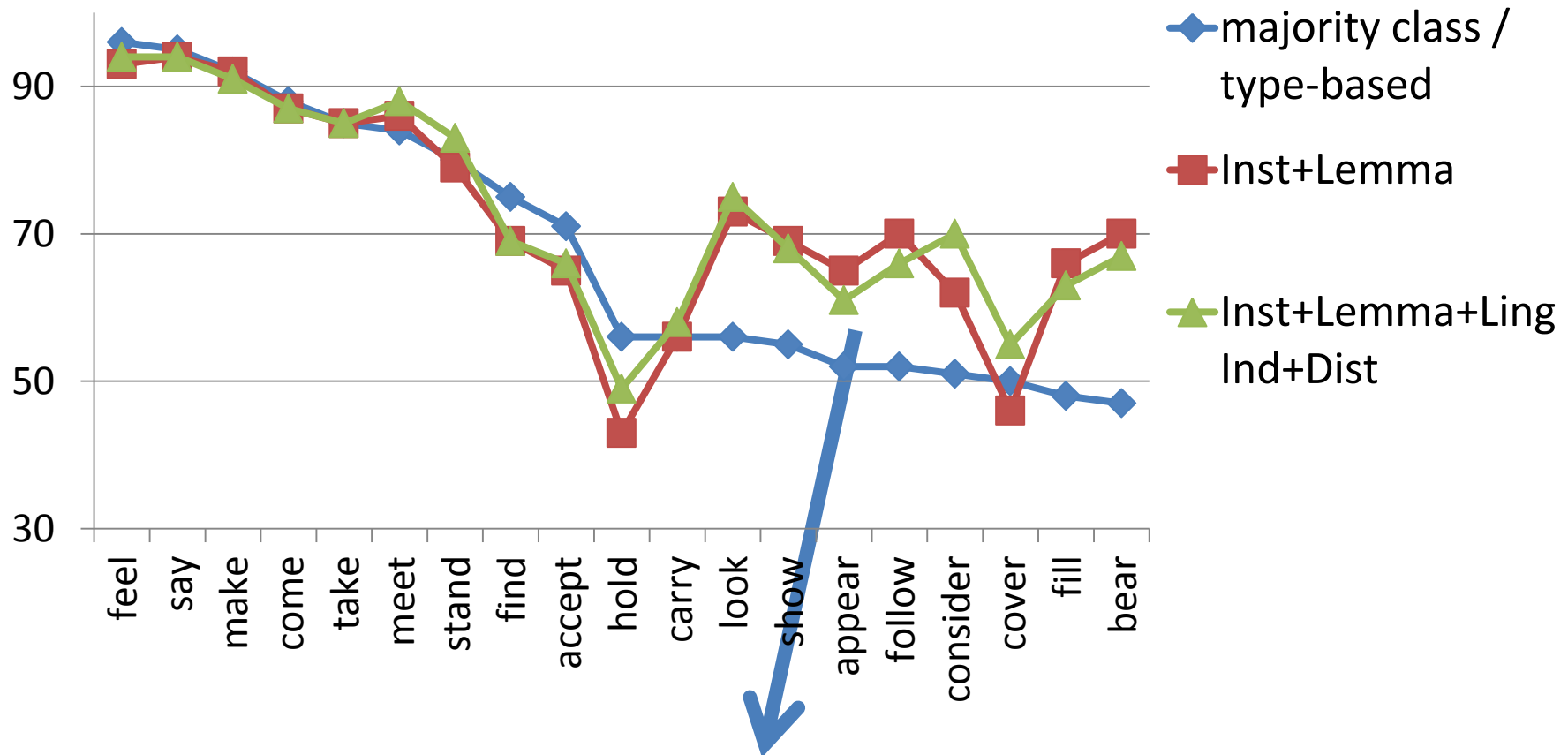
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Instance-based features do not generalize across verb types.

Experiment 4: INSTANCE-BASED classification



Experiment 4: INSTANCE-BASED classification



- The more ambiguous the verb, the more essential are instance-based features.
- Type-based features (bias) helpful?
 - depends on verb type

Summary:

Automatic prediction
of aspectual class of verbs in context

- if **no labeled training data** is available, can make type-based prediction with high accuracy.

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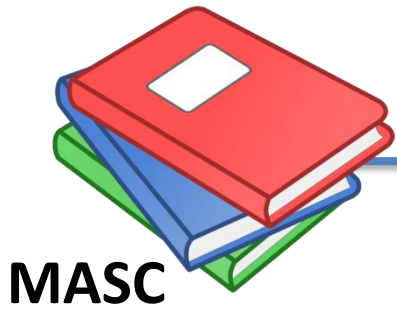
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treat different
verb types
differently

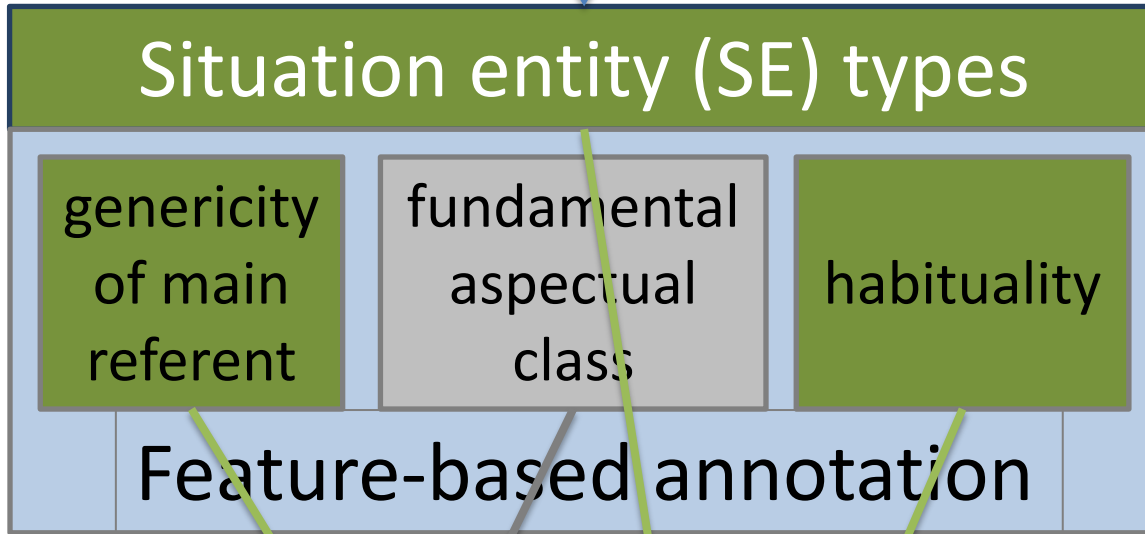


globally well-
performing
system

Overview



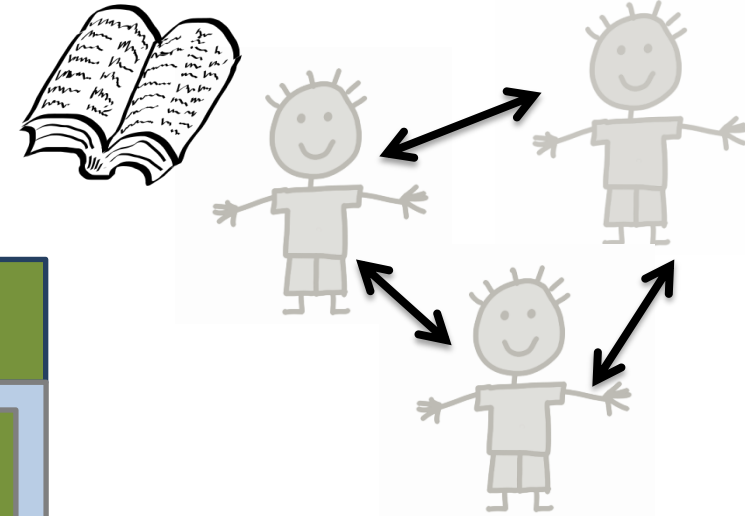
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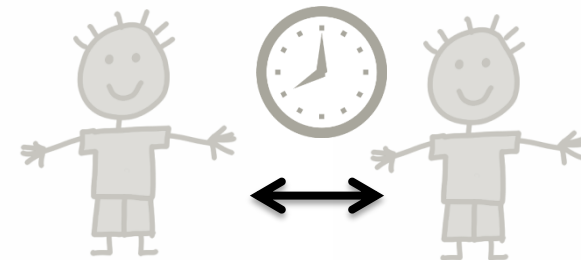
2) automatic classification

3) current status, ongoing & future work

1) Corpus annotation



inter-annotator
agreement



intra-annotator
consistency

Annotation status

Plan: gold standard via majority vote

→ label all clauses twice, have third annotator give annotations for disagreed segments (without seeing the other annotator's markup)

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corpus		# segments	2x	3x
MASC	news	3382	done	done
	essays	3357	done	done
	letters	2757	done	in progress
	jokes	4414	done	in progress
	fiction	5560	in progress	in progress
	journal	2581	in progress	in progress
	travel guides	4414	done	in progress
Wikipedia		8266	done	in progress

additional planned MASC sections: email (part), blog, non-fiction, technical

Future / Ongoing work: Automatic classification

- of **habituality**
- of the main referent's **genericity**
- of the clause's **situation entity type**

Future / Ongoing work: Automatic classification

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approach: combination of local features
with discourse-based features

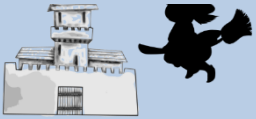
- extending upon Palmer et al. (2007)

Relevance of discourse modes

[Smith 2003]

- **future work:** create **annotated corpus** for discourse modes

NARRATIVE



EVENT,
STATE

REPORT



EVENT, STATE,
general statives

DESCRIPTION



EVENT,
STATE,
ongoing
EVENT

general statives

FACT, PROPOSITION,
general statives

INFORMATION



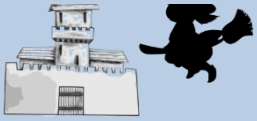
ARGUMENT



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[Smith 2003]

NARRATIVE



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FACT, PROPOSITION,
general statives

- **future work:** create **annotated corpus** for discourse modes
- **automatic classification** of discourse modes (using SE types & other features)

Relevance of discourse modes

[Smith 2003]



EVENT,
STATE

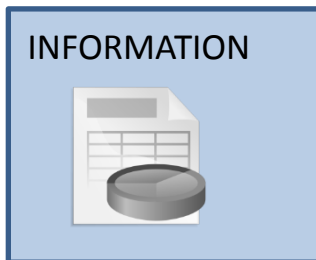


EVENT, STATE,
general statives

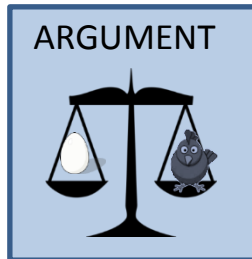


EVENT,
STATE,
ongoing
EVENT

general statives



FACT, PROPOSITION,
general statives



- **future work**: create **annotated corpus** for discourse modes
- **automatic classification** of discourse modes (using SE types & other features)
- ‘applications’
 - temporal processing of discourse
 - genre, stylistics
 - machine translation
 - argumentation mining

Future / ongoing work

Aspectual class of light verbs

have a heart attack vs. *have a daughter*
make sense vs. *make a cake*

frequent & ambiguous verbs, object matters

→ need a good solution to improve overall performance

→ does distributional information help?

Future / ongoing work

situation entity types

aspectual information

how speaker/writer presents a situation



**use of SEs in
different
languages?
relationships?**

Future / ongoing work

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aspectual information

how speaker/writer presents a situation



use of SEs in
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MT evaluation

Can we use SE type
information for evaluating
translation quality?
(start with related
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Situation entities in 汉语

aspectual information leads to default
interpretations of time in Chinese

[Smith & Erbaugh 2005]

→ inferring temporal information

[Zhang & Xue 2014]

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[Smith & Erbaugh 2005]

→ inferring temporal information

[Zhang & Xue 2014]

→ develop annotation scheme

→ compare use of SE types / features
vs. English

<http://sitent.coli.uni-saarland.de>

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Ruth Kühn

Fernando Ardente

Christine Bocionek

We are



*to hear your
suggestions or
ideas for
collaborations.*

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Carlson, Gregory N. "Truth conditions of generic sentences: Two contrasting views." *The generic book* (1995): 224-237.

Situation entity annotation

BACKUP SLIDES

Future / Ongoing work:

Aspectual class of **light verbs**

- For some frequent & ambiguous verbs, the object matters → need a good solution to improve overall performance
 - *have a heart attack* ↔ *have a daughter*
 - *make sense* ↔ *make a cake*
- Idea: using distributional information
- M.Sc. thesis 2015 (Liesa Heuschkel)

Future / Ongoing work:

Eventuality information in **Chinese**

- boundedness of events/states leads to default interpretations of time in Chinese (Smith & Erbaugh 2005)
- potentially useful for inferring temporal information (Zhang & Xue 2014)
- Develop annotation scheme, compare use of situation entity types vs. English
- M.Sc. thesis 2015 (Bryan Zhang)

Future / Ongoing work:

Machine Translation evaluation

- situation entity types
 - aspectual information
 - how speaker/writer presents a situation
- **Question 1:** relation between SE types in different languages (e.g. German-English, French-English)
- **Question 2:** can we use SE type information for evaluating translation quality?
- M.Sc. thesis 2015 (Kleo Mavridou)

Segmentation post-processing

- merge situationless segments with appropriate neighboring segment, respecting parse trees. (automatic)

verbless segments

For every dollar
donated to Goodwill in 1998,
we helped our “graduates” earn an estimated \$102.



For every dollar donated to Goodwill in 1998,
we helped our “graduates” earn an estimated \$102.

Segmentation post-processing

- merge situationless segments with appropriate neighboring segment, respecting parse trees. (manual)

to-infinitives

She has learned
to make her own money.



She has learned to make her own money.

Segmentation post-processing

cases requiring manual merging

So the shift in the image of Gates has been an interesting one for me to watch.



So the shift in the image of Gates has been an interesting one for me to watch.

- multiple situations per segment

genericity of main referent -- disagreements

- 183 cases, B&C marked *specific*, A marked *generic*, judged by authors:
 - 50 (27.3%) *both readings possible*
 - 69 (37.7%) *specific*
 - 22 (12%) *generic*
 - 36 (19.7%) *not sure given the context 5 segmentation problems*
 - 1 (0.5%) *expletive*

genericity of main referent -- disagreements

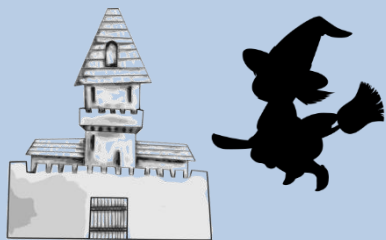
- Cases marked generic by A, which should be specific:
 - simple plurals
 - But **some regulations**, aimed at specific regional problems...
 - **Some of his fellow historians** question ...
 - specific concepts
 - **a humanitarian crisis** that has festered since the Gulf War
 - you (either reading possible)
 - if **you** have the will and dedication here, **you** can learn a lot

genericity of main referent -- disagreements

- Cases marked generic by A, which should be generic:
 - Under the plan, **unsecured creditors** would receive about \$92 million,...
 - **Chinese hot and sour soup** often includes bitter melon.
 - ... in **many regions of the world** that boast moderate to warm climates.

Modes of discourse [Smith 2003]

NARRATIVE



temporal progression

**EVENT,
STATE**

REPORT



temporal progression,
related to speech time

**EVENT, STATE,
general statives**

DESCRIPTION



spatial progression

**EVENT, STATE,
ongoing EVENT**

INFORMATION



**general
statives**

atemporal, metaphoric progression

ARGUMENT



**FACT,
PROPOSITION,
general statives**

Feature: genericity of main referent (inter-annotator agreement)

183 clauses: B & C agree, A disagrees

92%: B & C → specific, A → generic

40%:
misunder-
standing by A

30%:
multiple
readings

30%:
other

As a governor, I'll make sure
that every kid in New York has the
same opportunity.

you in letters → generic or addressee?



annotators with different preferences:
identify ambiguous cases

Comparing B and C: 2358

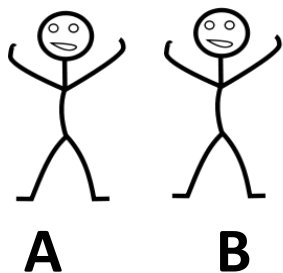
segments : specific by both

- 122 segments: generic by at least one
- 43 segments: generic by both

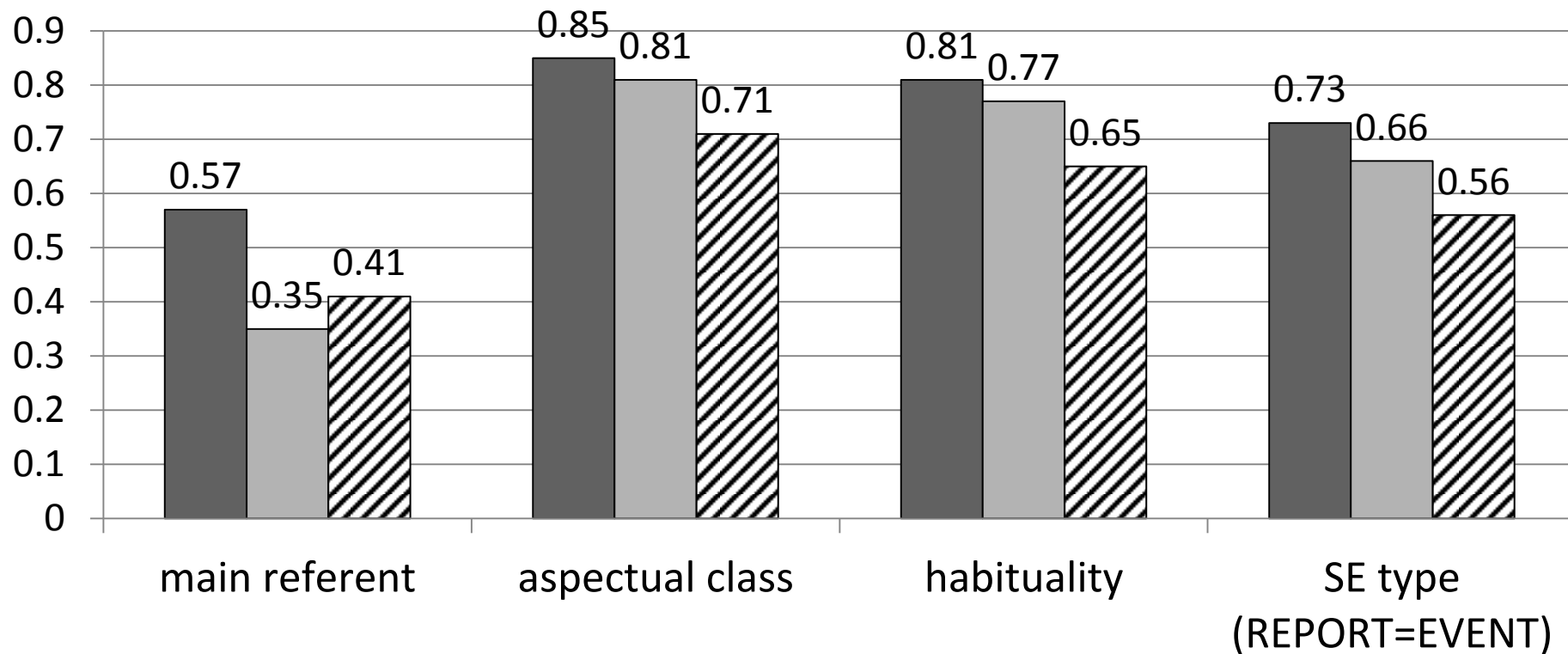
➡ very few cases, cannot
draw conclusions on
reasons for low κ yet.

➡ follow-up study with data
targeting generics in
progress

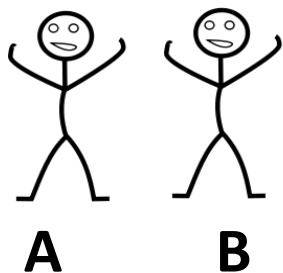
Inter-annotator agreement: genres



MASC ■ jokes ■ news ▨ letters

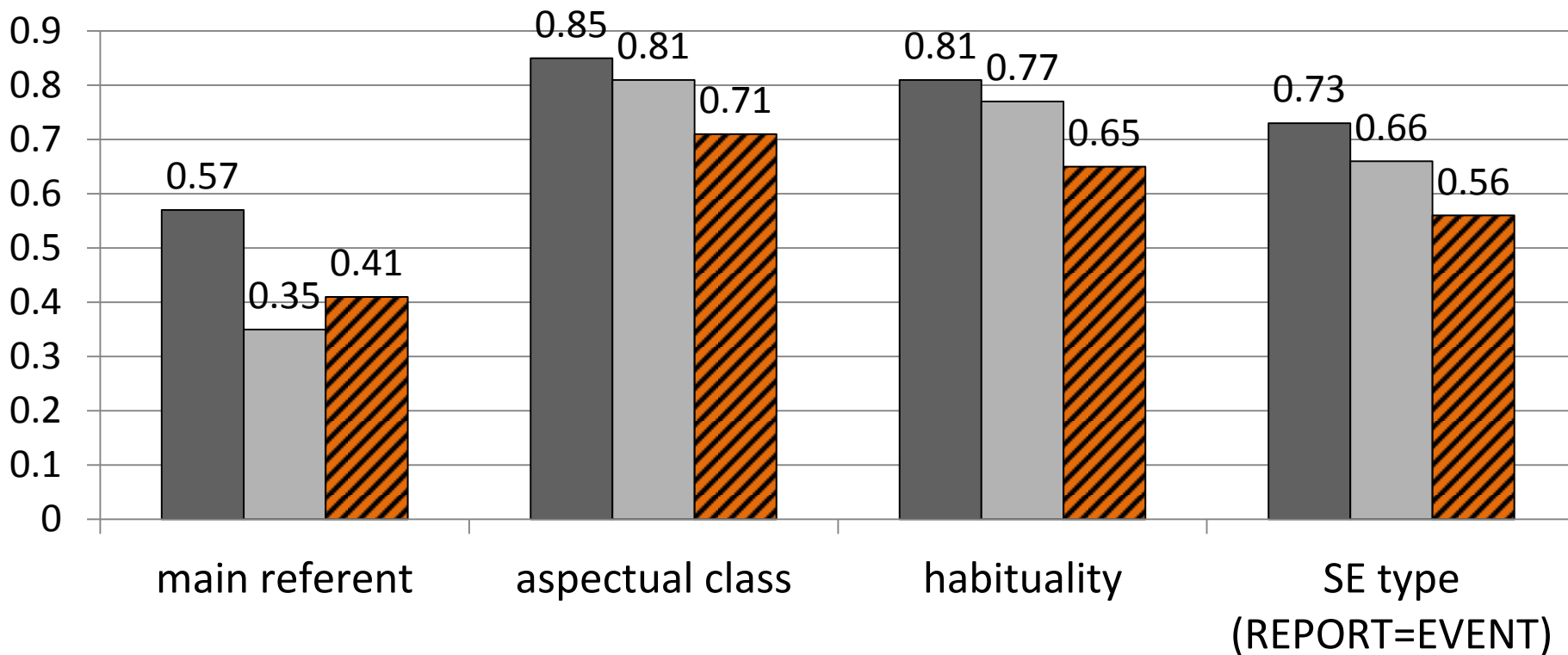


Inter-annotator agreement: genres



Why is agreement lower on letters subsection?

MASC ■ jokes ■ news ■ letters



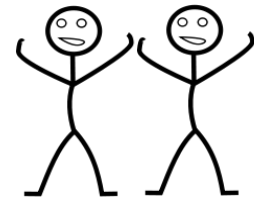
Generics follow-up study

- address the issue of *sparsity*: enrich corpus with documents where we expect a higher proportion of general statives
- **Wikipedia documents**: agreement study
 - (corpus total: about 8200 situations)

category	# situations	Fleiss' κ , main referent	Fleiss' κ , SE type
animals	160	0.65	0.71
games	159	0.71	0.55
gangs	255	0.23	0.58
history	485	0.10	0.57
sports	508	0.62	0.67
tribes	167	0.45	0.57
<i>average/total</i>	1808	0.64	0.67

Features: inter-annotator agreement

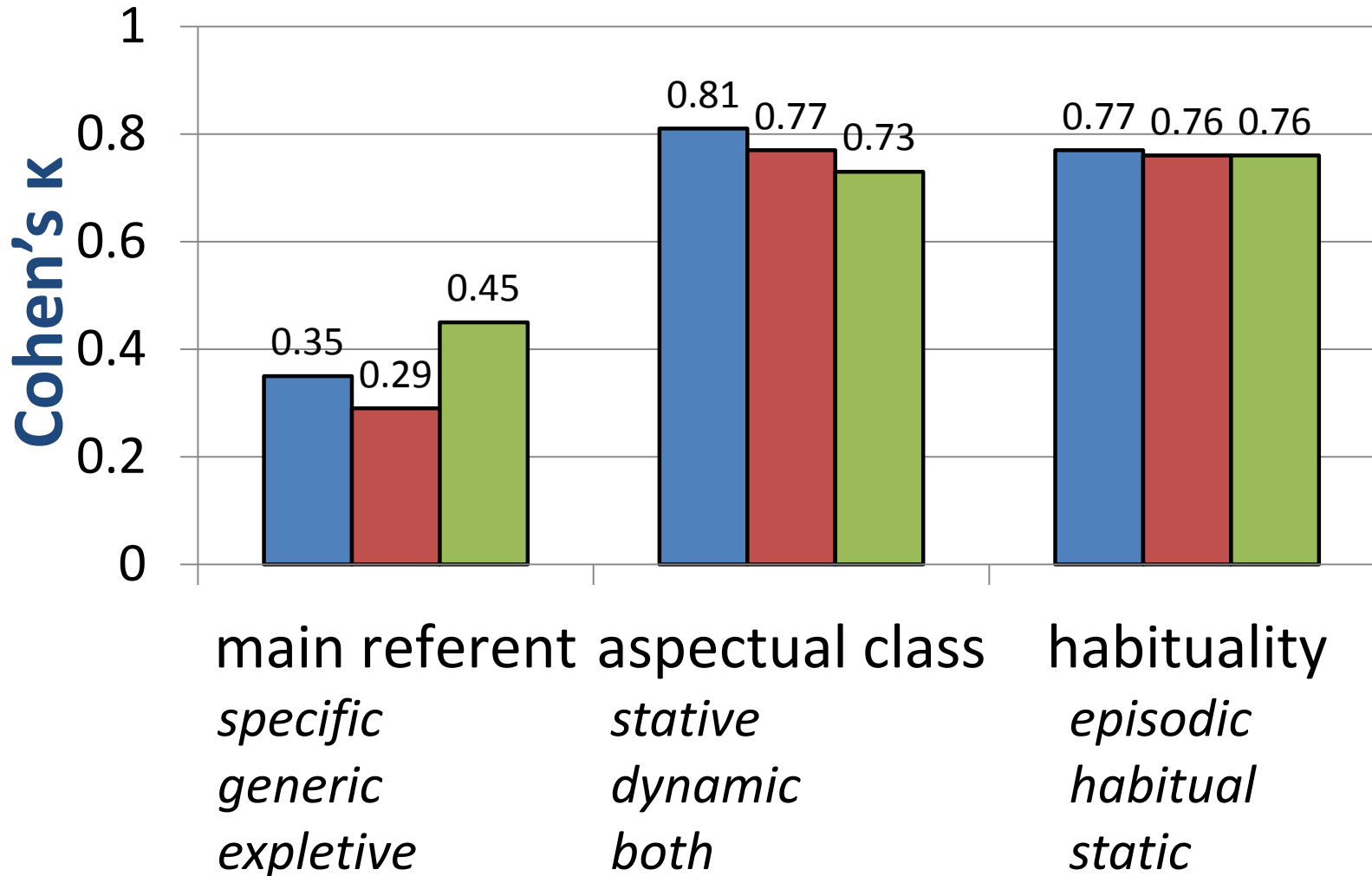
MASC: news



■ A:B

■ A:C

■ B:C



Generics follow-up study

address the issue of **clarity**: compared definition to existing theories & corpora, clarified definition in manual, added examples.

Generic noun phrases (theory applied to subjects):

(compare to Krifka et al. 1995: “The Generic Book”)

kind-referring: *The lion disappeared from Asia.*

nonspecific, referring to arbitrary member of kind:

A lion roars when it smells food.

ACE-2005:

GEN ≈ generic

SPC ≈ non-generic

NEG → negated

No lawyer would...

USP = underspecified ≈ non-generic

non-generic nonspecific reference:

Many people will come.

mention of entities whose identity would be hard to locate:

Officials said ...

→ difficult to annotate,
especially for non-subjects
(story is different,
see Krifka et al. 1995)

→ only 1567 GEN subjects.

Wikipedia documents: agreement

- WikiGen corpus: 49 documents (≈ 8200 situations)
- agreement study: 14 documents (≈ 1800 situations)

annotators	main referent	aspectual class	habituality	SE type
A1, A2	0.61	0.65	0.65	0.68
A1, A3	0.60	0.63	0.64	0.65
A2, A3	0.70	0.68	0.60	0.69
all, Fleiss' κ	0.64	0.66	0.63	0.67

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