Computerlinguistik Kolloquium

Potsdam, November 2014

Annotation and automatic classification of situation entity types

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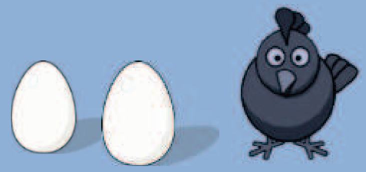
Situation entity types [Smith 2003]

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

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

Modes of discourse [Smith 2003]



NARRATIVE

Modes of discourse [Smith 2003]

NARRATIVE

INFORMATION

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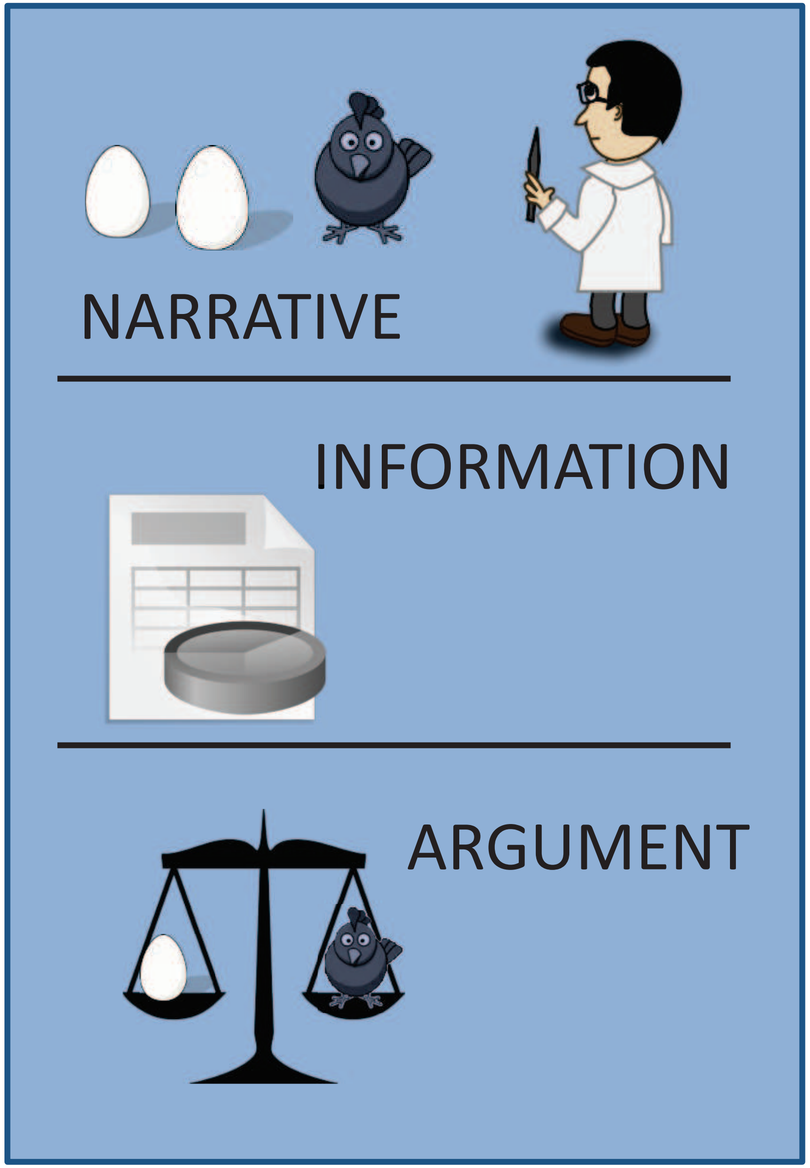

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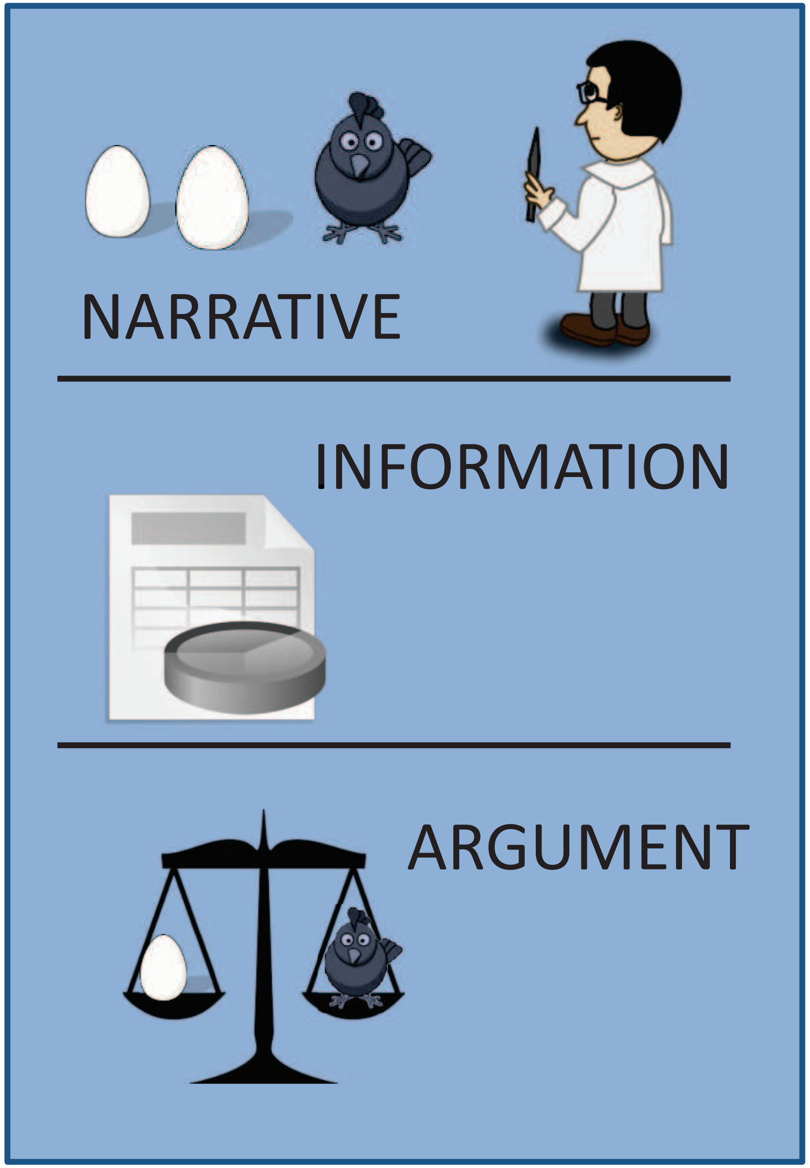

Different passages of a text can have different discourse modes.

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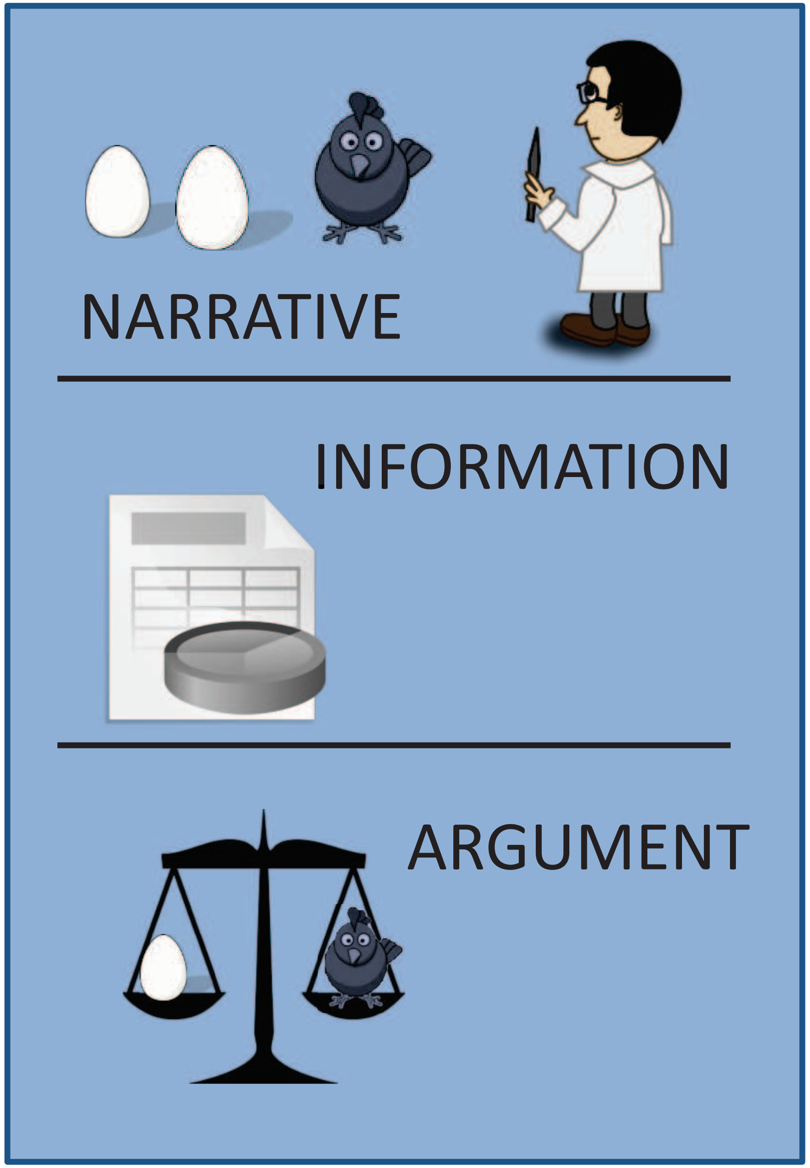


Different passages of a text can have different discourse modes.

one text ≈ one genre

one text ≠ one discourse mode

related: Werlich's typology of texts (1975)

Modes of discourse [Smith 2003]

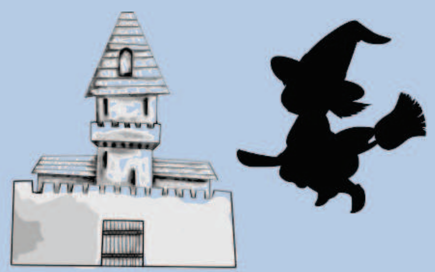
NARRATIVE

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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EVENT, STATE,
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DESCRIPTION

spatial progression

EVENT, STATE,
ongoing EVENT

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FACT,
PROPOSITION,
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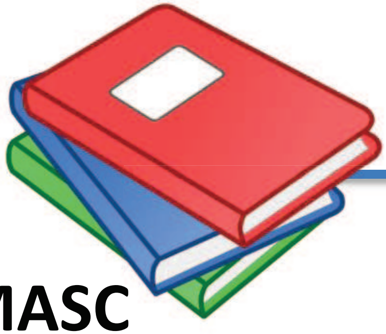
atemporal, metaphoric progression

Overview

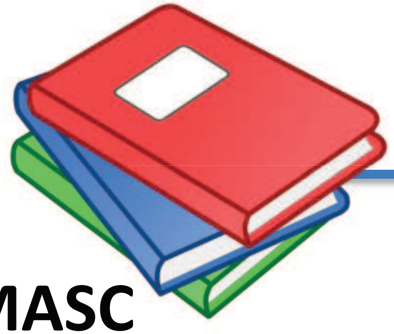


MASC

(automatic) segmentation

Situation entity (SE) types

Overview



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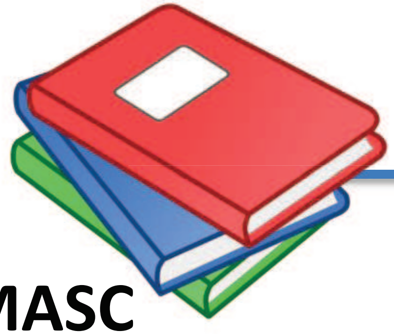
Situation entity (SE) types

genericity of main referent	fundamental aspectual class	habituality

Feature-based annotation

Overview



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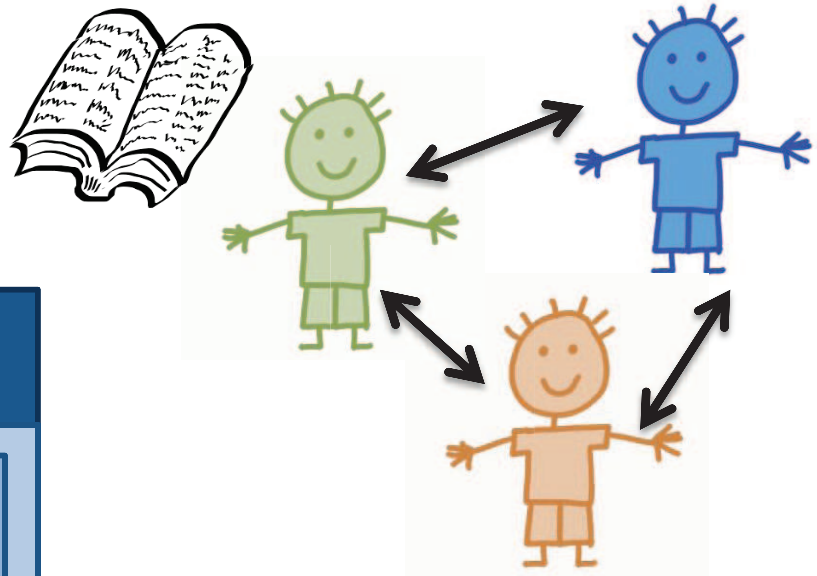
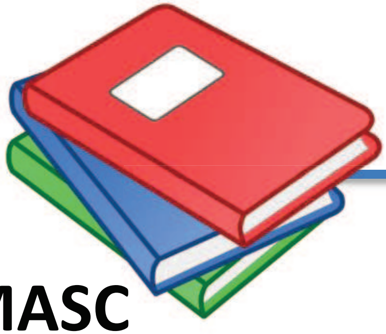


inter-annotator agreement

Overview



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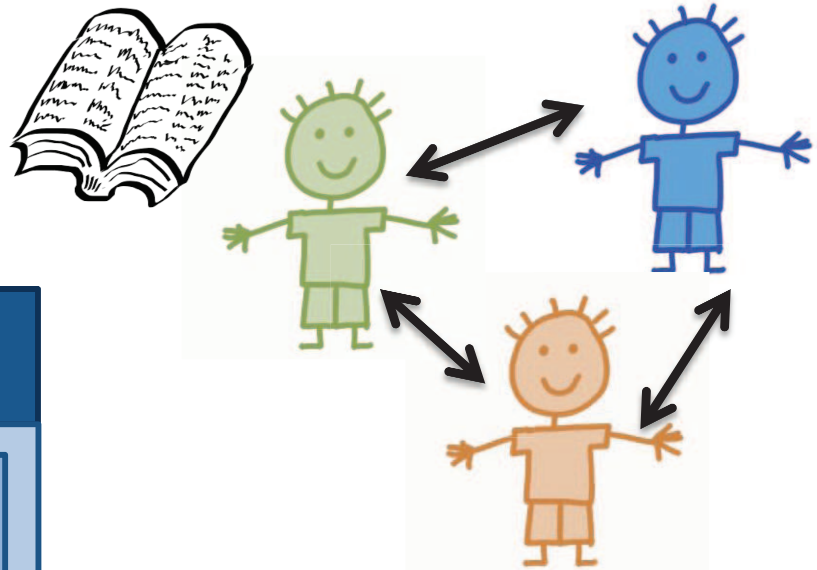

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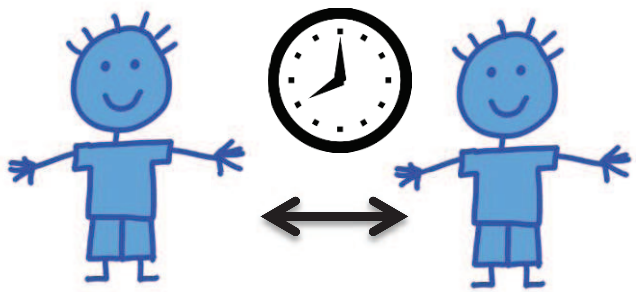

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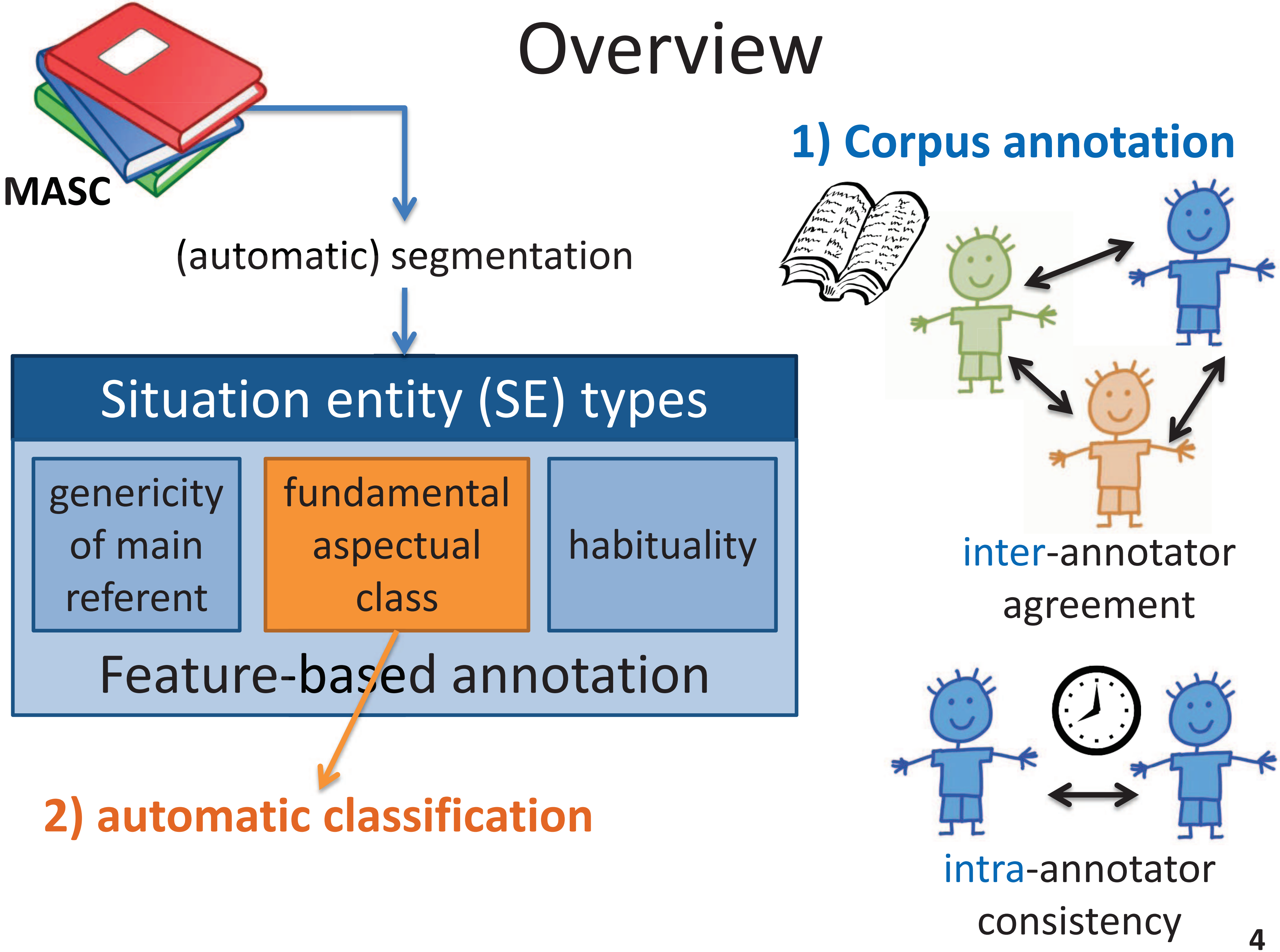
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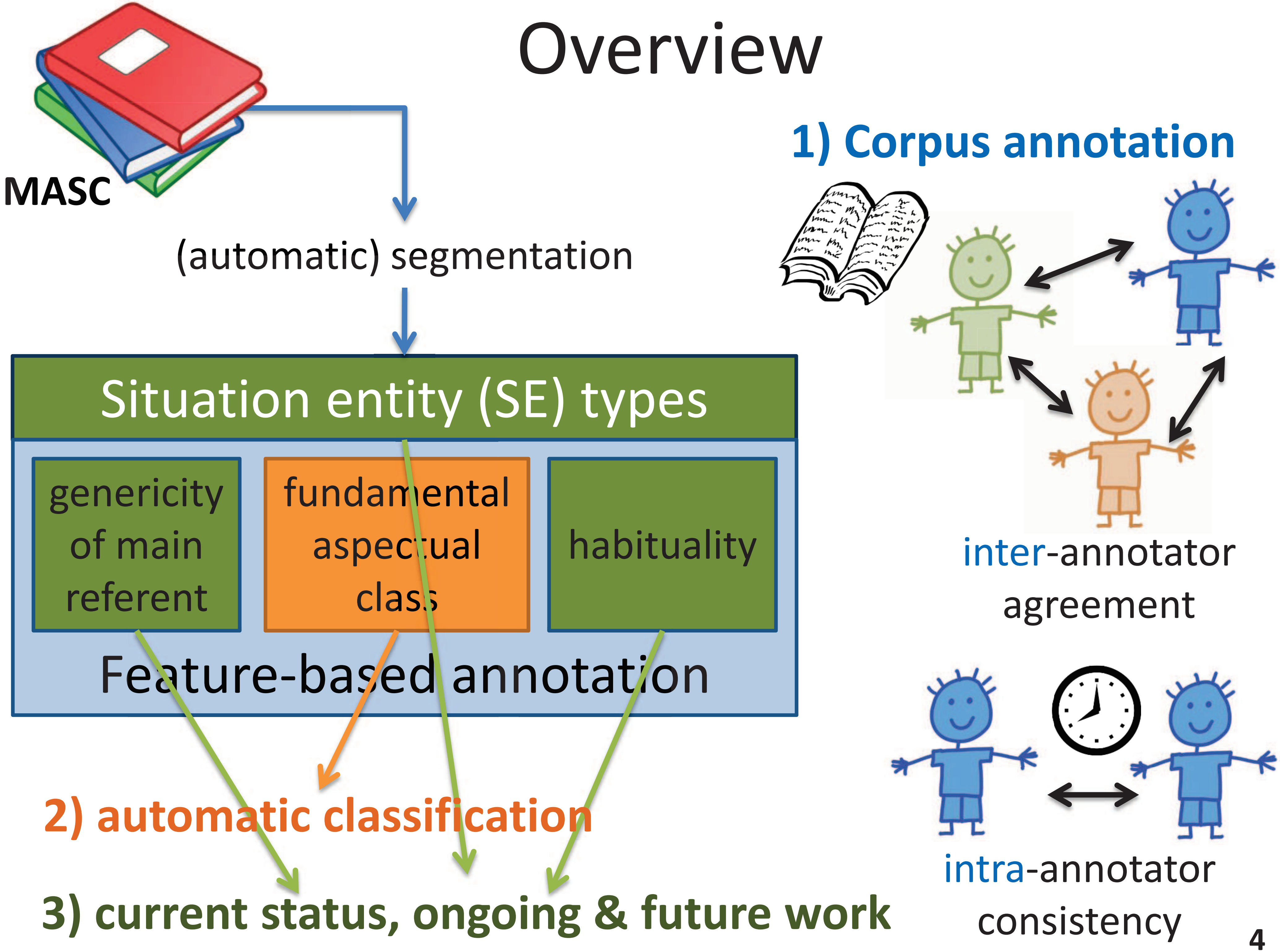
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2) automatic classification
3) current status, ongoing & future work

Motivation of annotation study

assess the applicability of SE type classification as described by Smith [2003]

borderline cases? human agreement?

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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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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

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

Related work

- Palmer et al. [2007]:
  - first labeled data set for SEs
  - ~6000 clauses
  - no annotation manual
  - Cohen's $\kappa = 0.54$

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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

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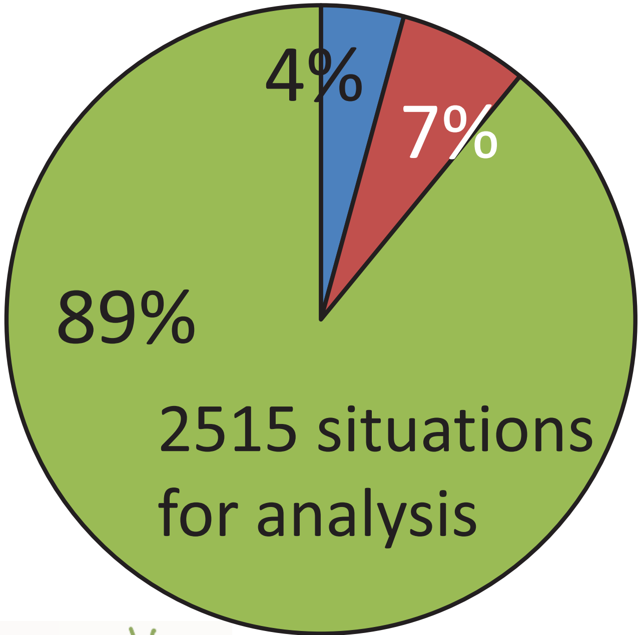

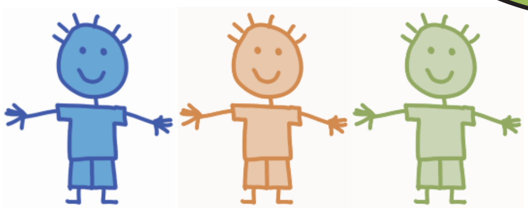

MASC news: 2823 segments

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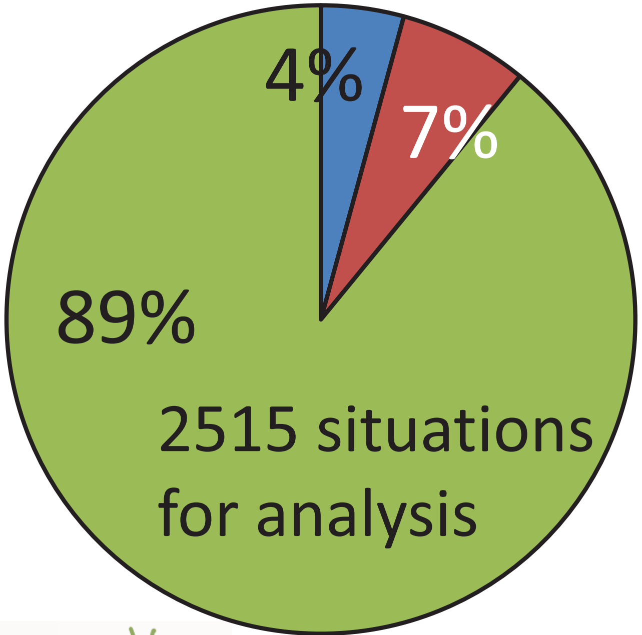

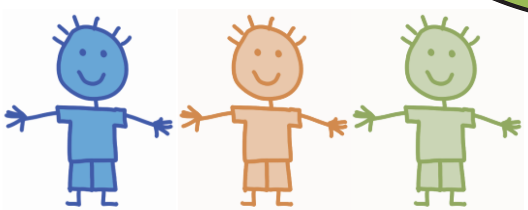

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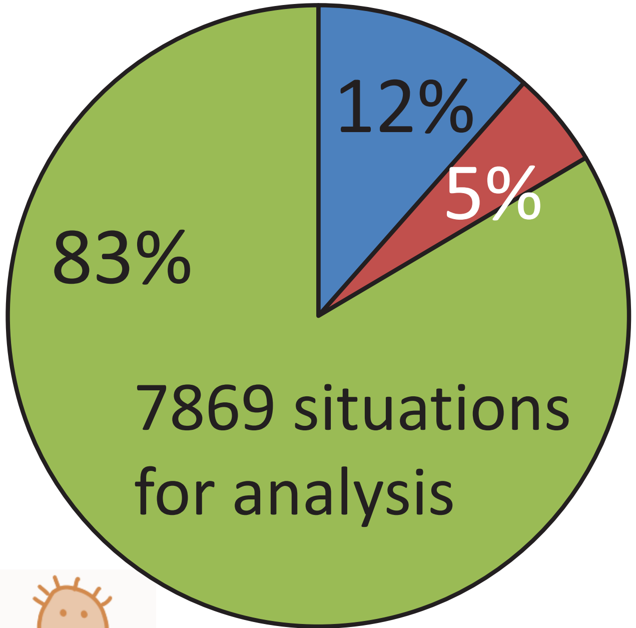

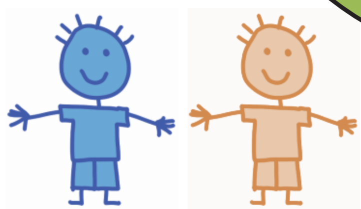

MASC news, jokes, letters: 9428 segments

Feature-driven annotation

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2 determine **feature values**

genericity of main referent	fundamental aspectual class	habituality

Which features distinguish the SE types from each other?

Feature-driven annotation

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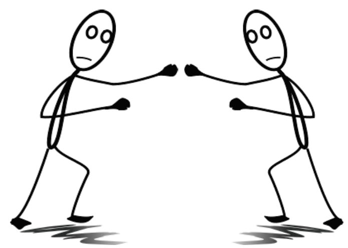
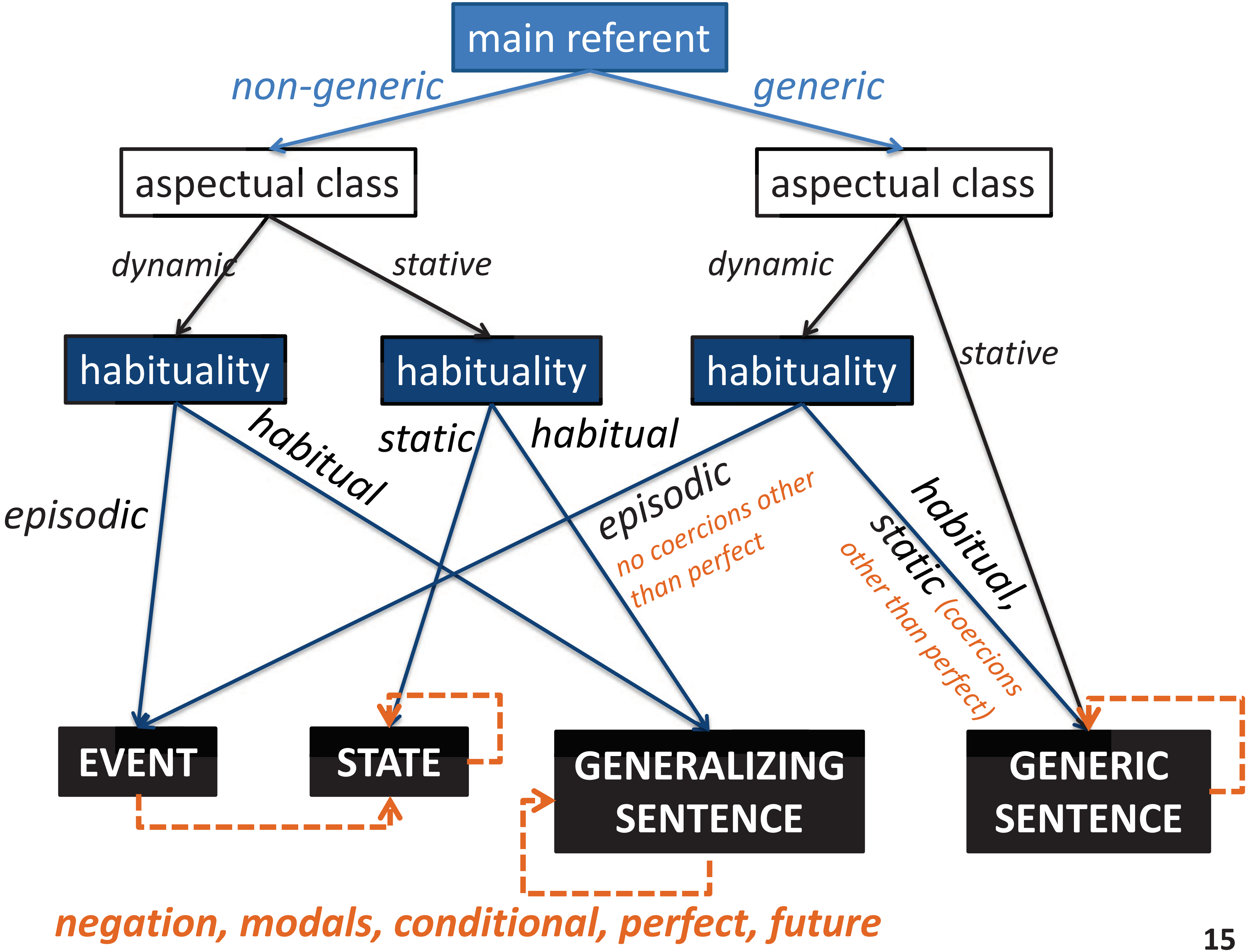
✓ analyze disagreements





main referent
non-generic
generic
aspectual class
aspectual class
dynamic
stative
dynamic
stative
habituality
habituality
habituality
episodic
habitual
static
habitual
episodic
no coercions other than perfect
habitual,
static (coercions other than perfect)
EVENT
STATE
GENERALIZING SENTENCE
GENERIC SENTENCE
negation, modals, conditional, perfect, future

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.

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

[Friedrich & Palmer, ACL 2014]

Feature: fundamental aspectual class

feature of the entire clause,
marks main verb.

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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**

[Friedrich & Palmer, ACL 2014]

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distinguishes
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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.

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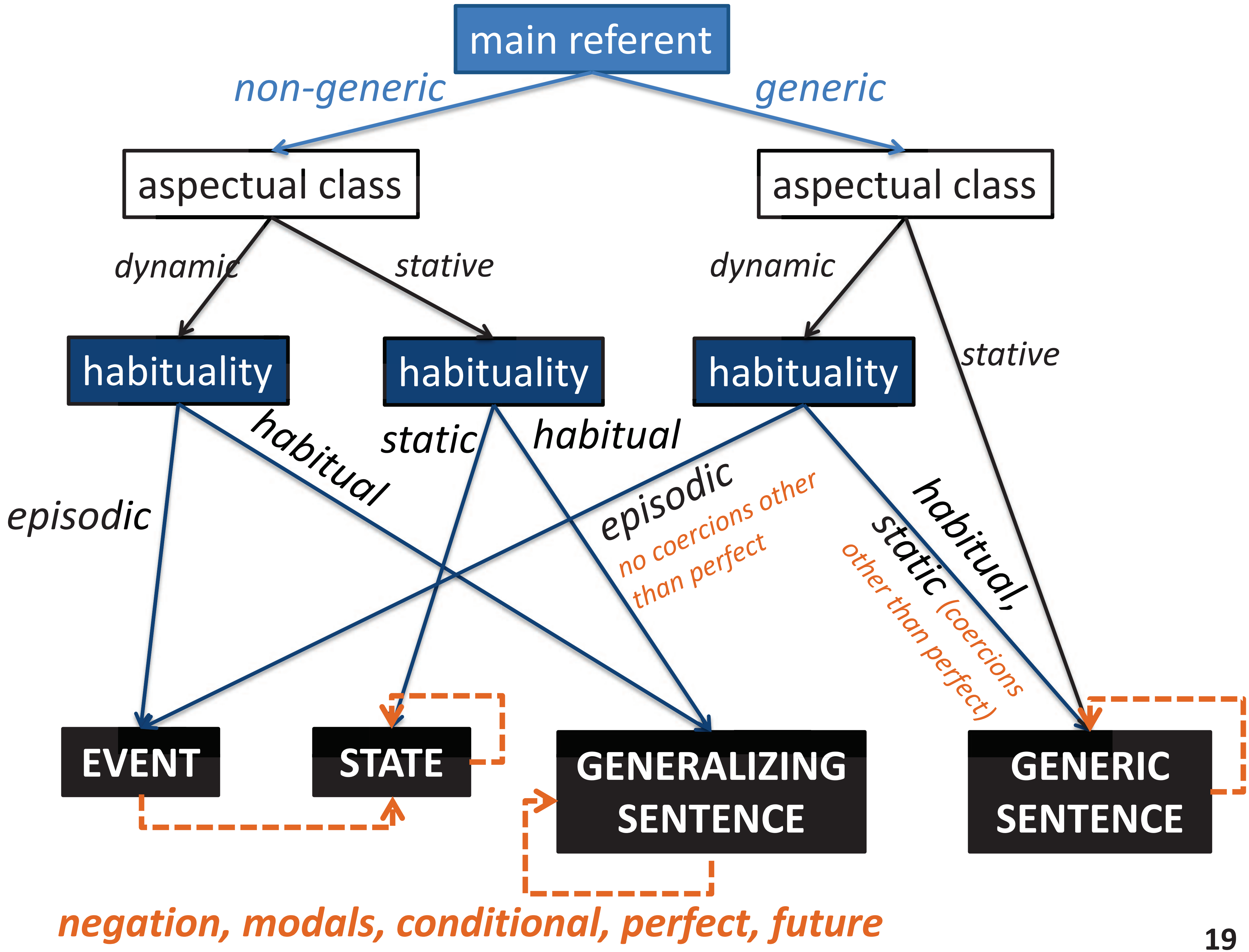
Mary fed her cats this morning.	**episodic**: one-time event
Mary feeds her cats every morning.	**habitual**: regularity
Glass breaks easily.	**habitual**: regularity
Mary owns four cats.	**static**: for STATEs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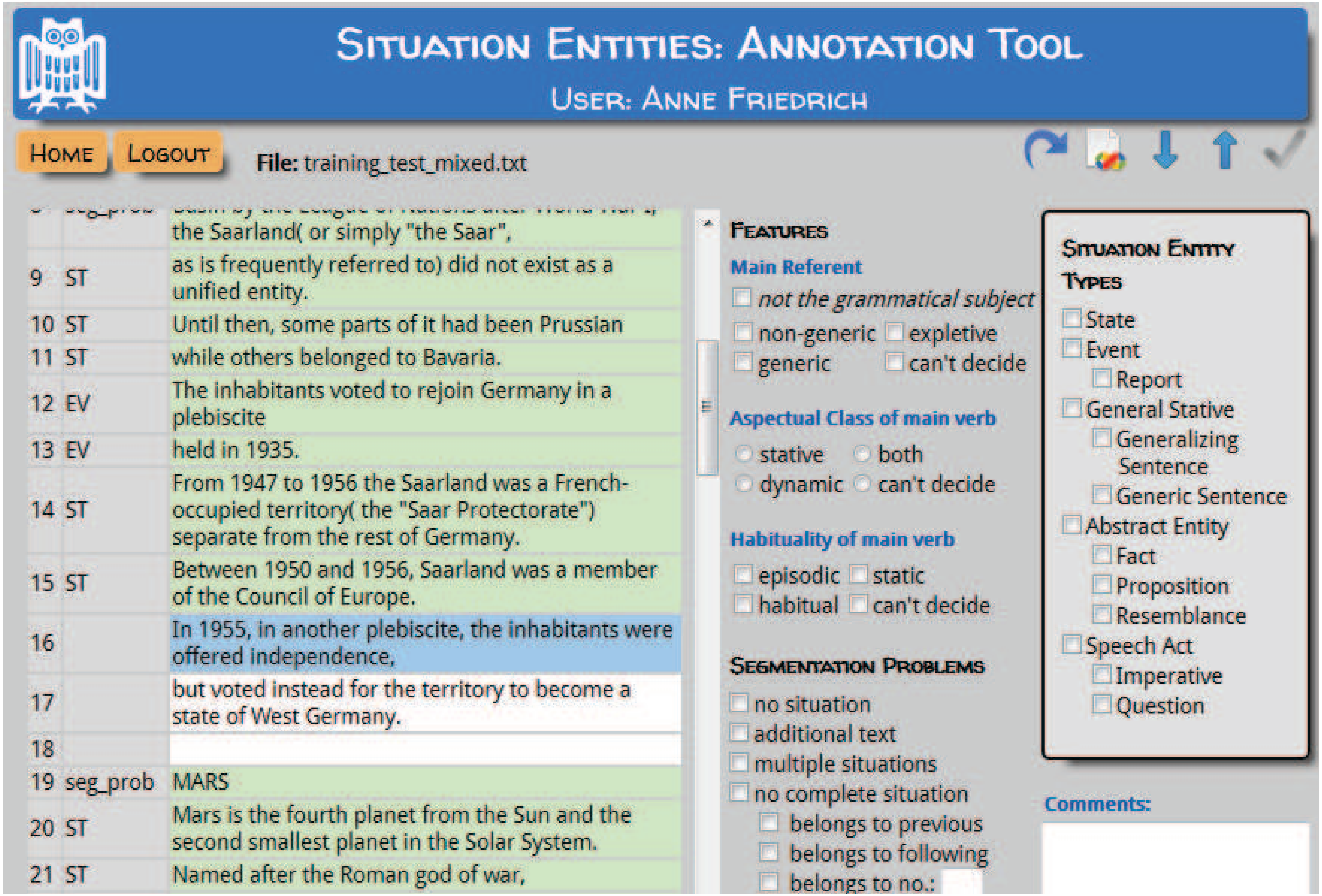
Situation Entities: Annotation Tool
User: Anne Friedrich
Home
Logout
File: training_test_mixed.txt
the Saarland(or simply "the Saar",
9 ST as is frequently referred to) did not exist as a unified entity.
10 ST Until then, some parts of it had been Prussian
11 ST while others belonged to Bavaria.
12 EV 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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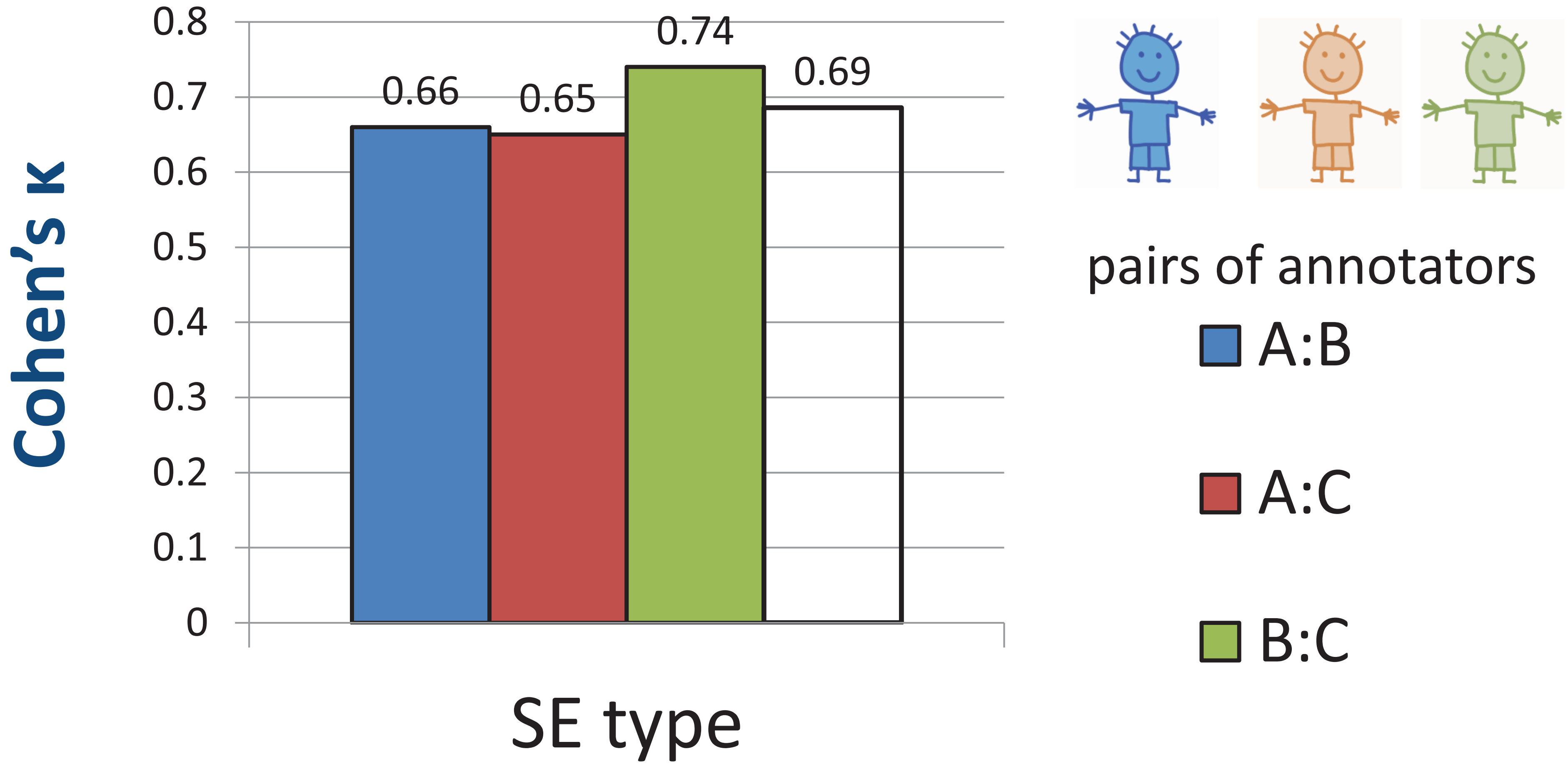
- identifying generic noun phrases [Reiter & Frank 2010]
- identifying habitual vs. episodic sentences

  [Mathew & Katz 2009]

SE types: inter-annotator agreement

labels: STATE, EVENT, GENERIC SENTENCE, GENERALIZING SENTENCE

MASC: news (2823 situations)



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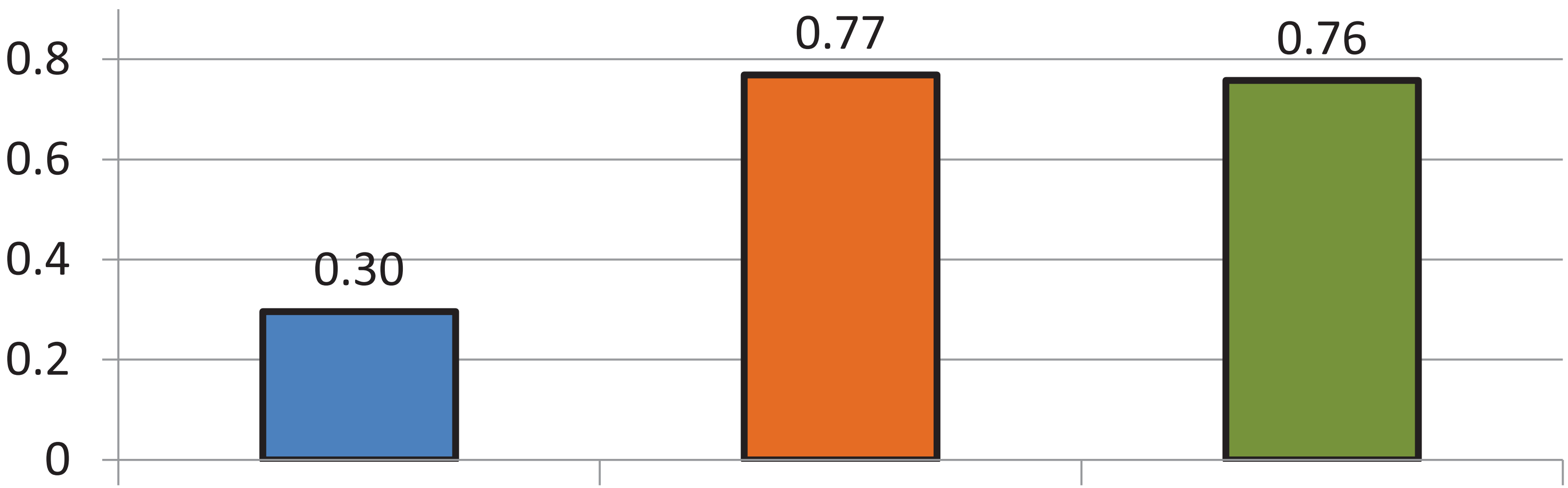
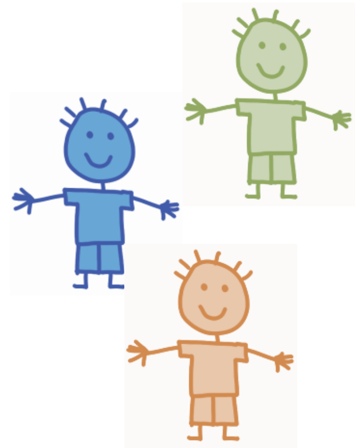
Fleiss' κ



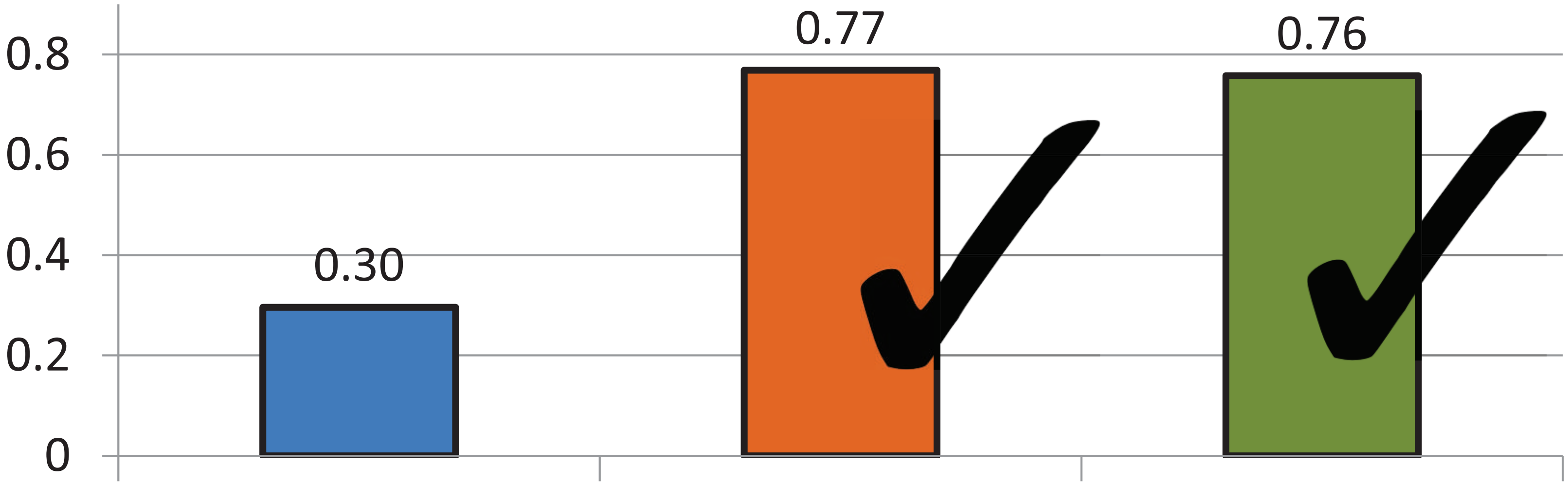


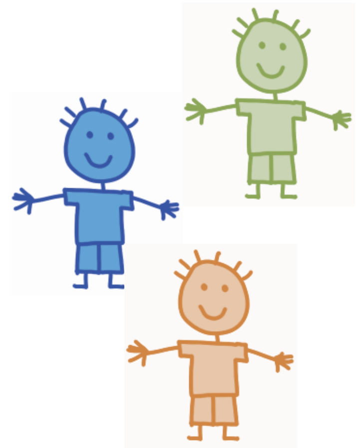
main referent	**aspectual class**	**habituality**
specific	*stative*	*episodic*
generic	*dynamic*	*habitual*
expletive	*both*	*static*

Features: inter-annotator agreement

MASC: news (2823 situations)

Fleiss' κ

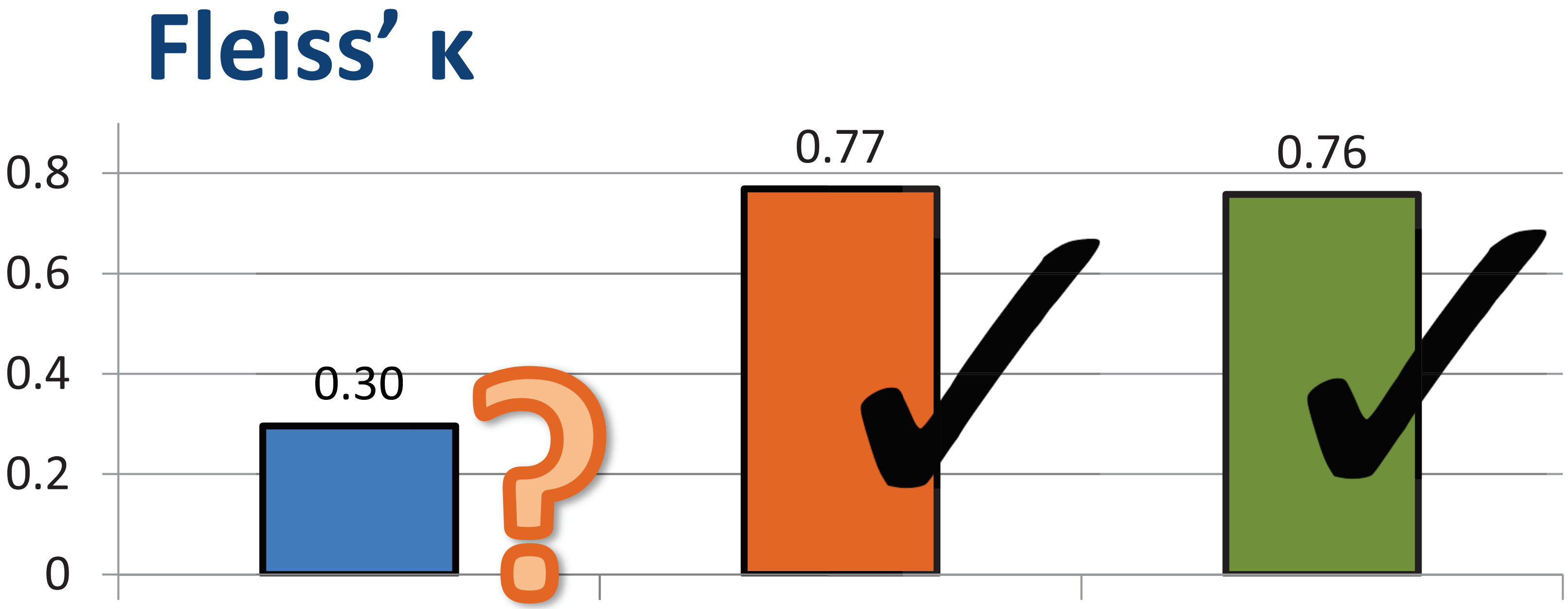




main referent	**aspectual class**	**habituality**
specific	*stative*	*episodic*
generic	*dynamic*	*habitual*
expletive	*both*	*static*

Features: inter-annotator agreement

MASC: news (2823 situations)



main referent

specific
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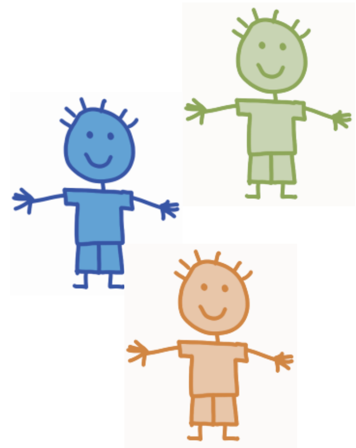
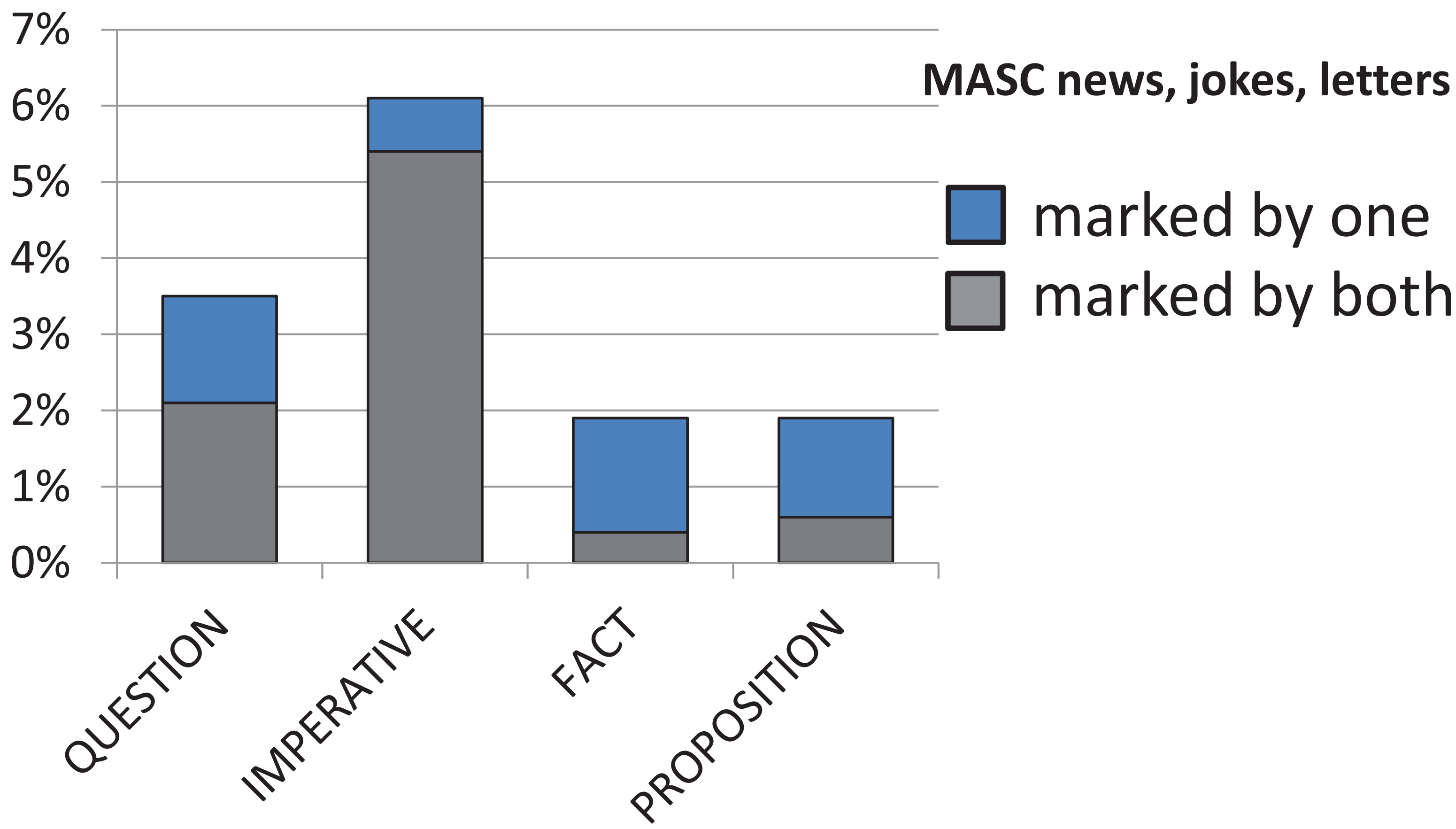


% of situations marked as speech acts / abstract entities:



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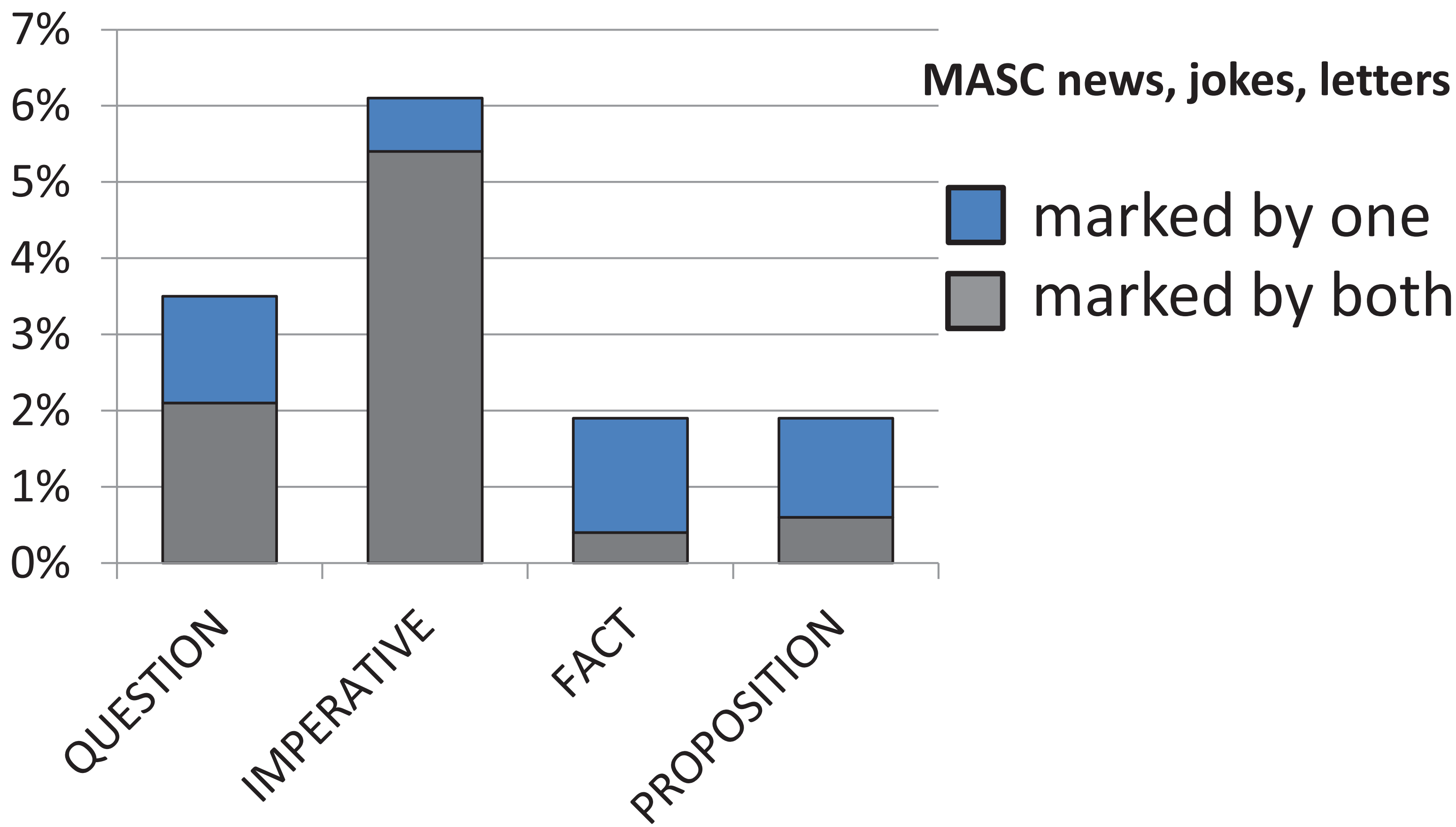

indirect questions?

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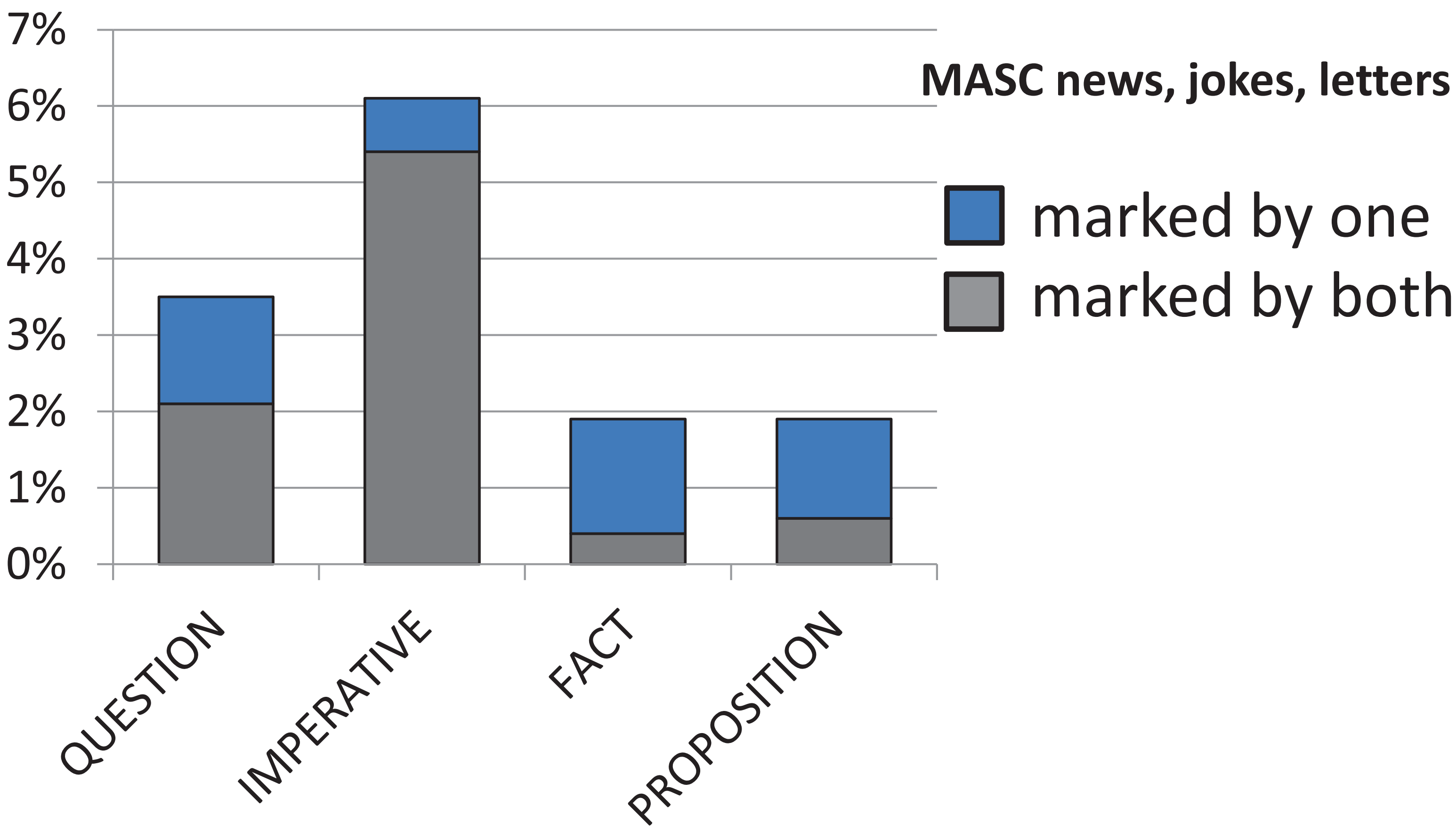
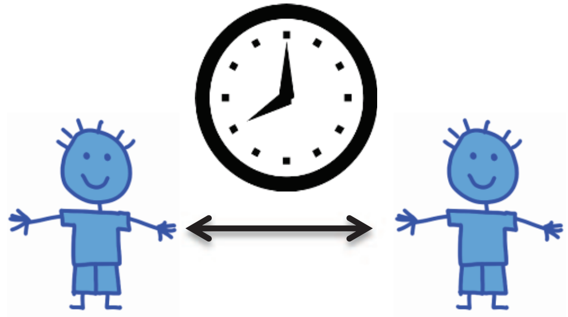


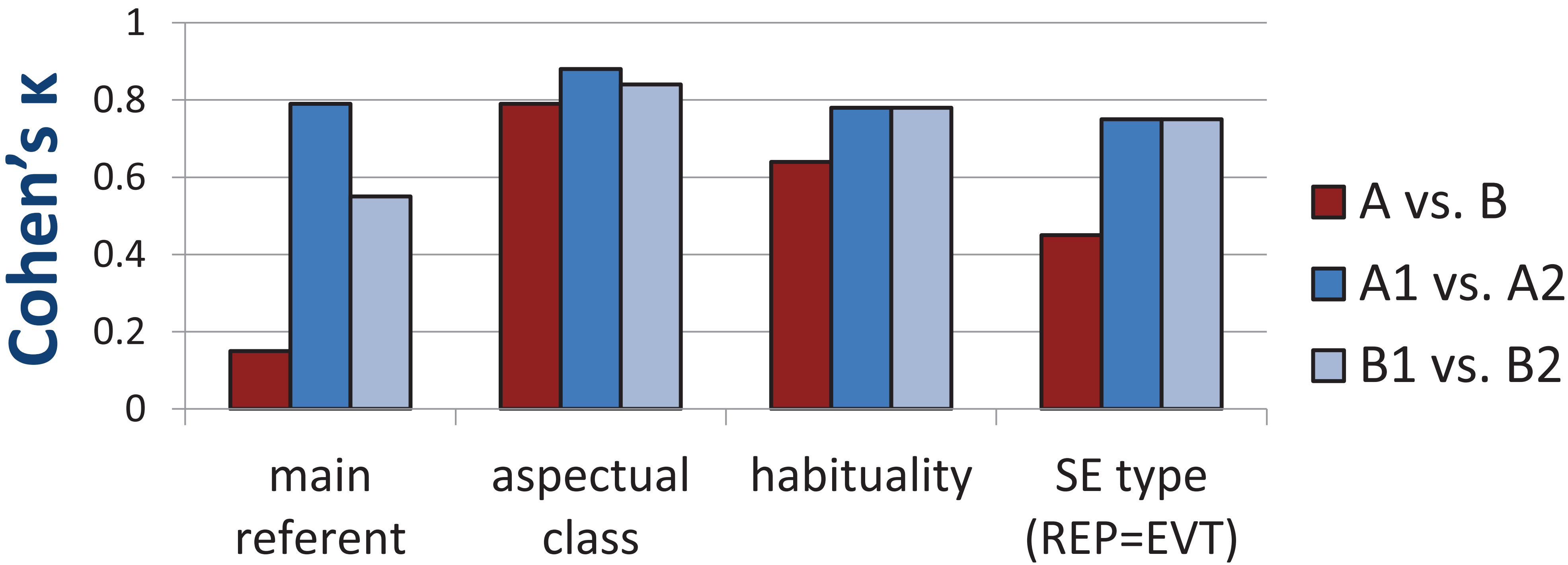
indirect questions?

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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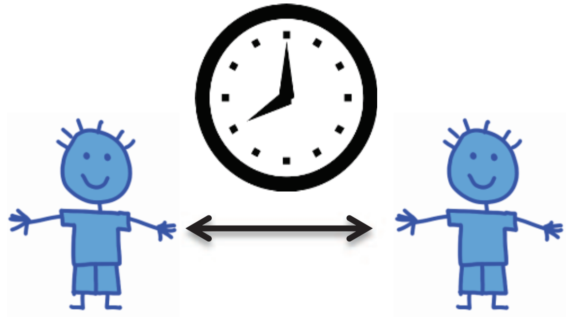

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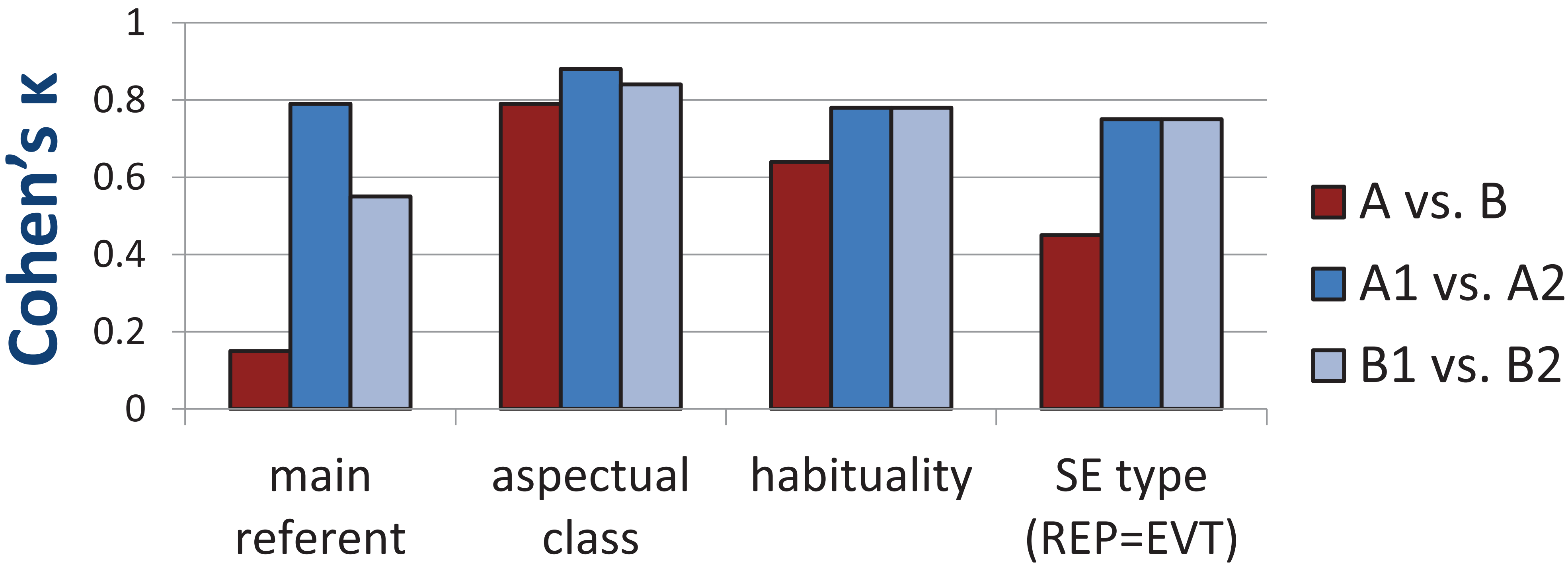


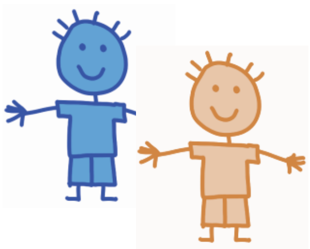
→ intra-agreement > inter-agreement

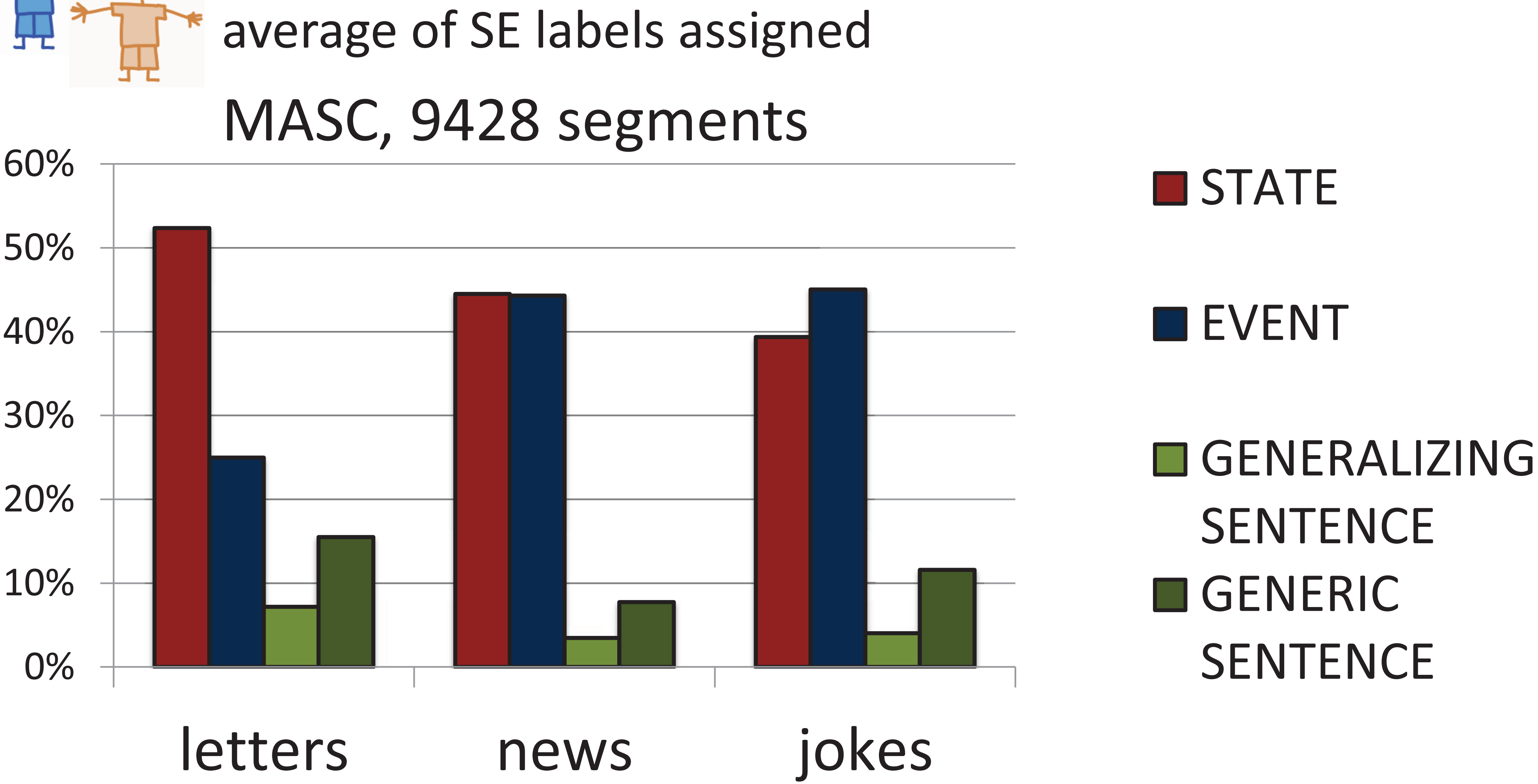
→different understanding of some cases

→ 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





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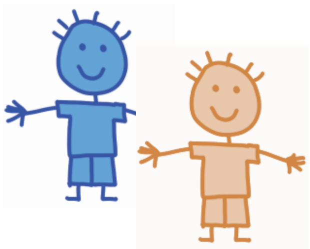
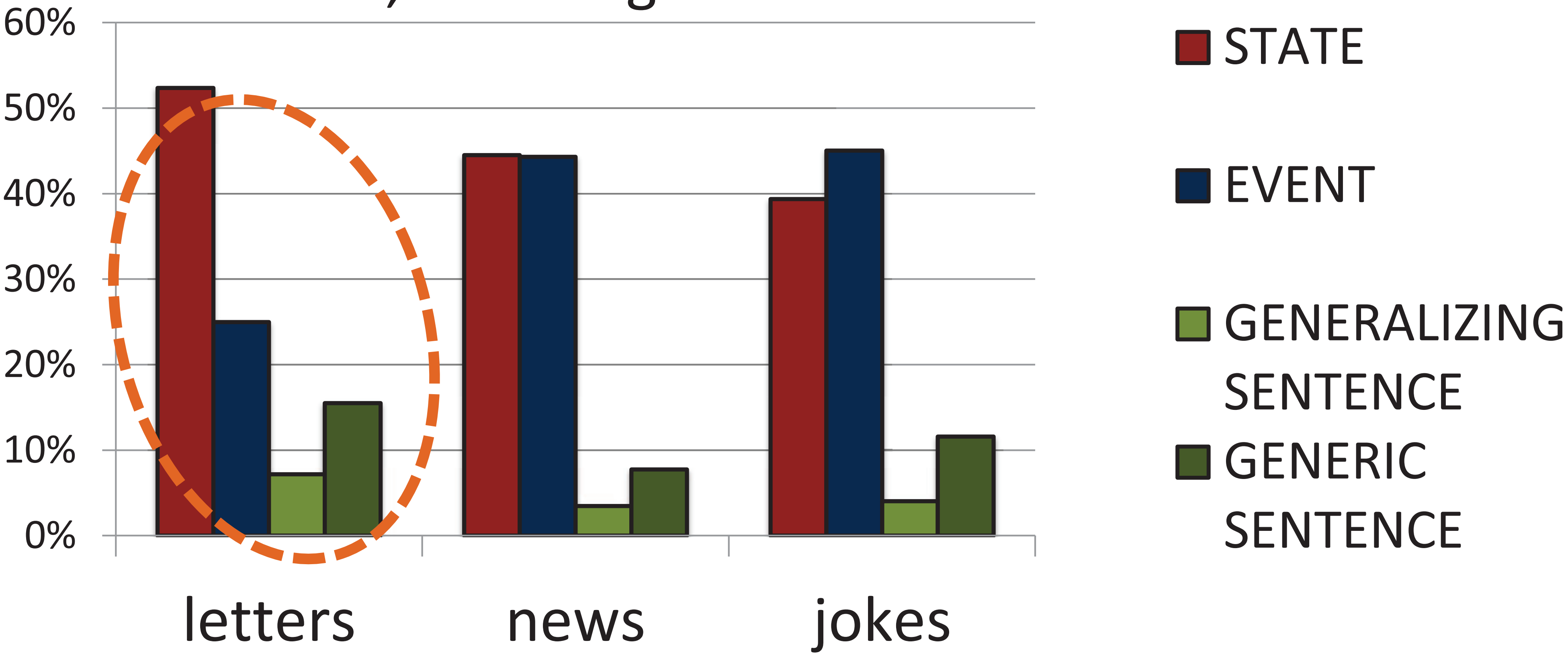


average of SE labels assigned

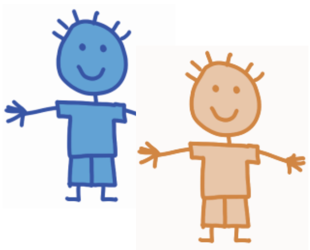
MASC, 9428 segments



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

Distribution of SE types: genres

more details: [Palmer & Friedrich, 2014]



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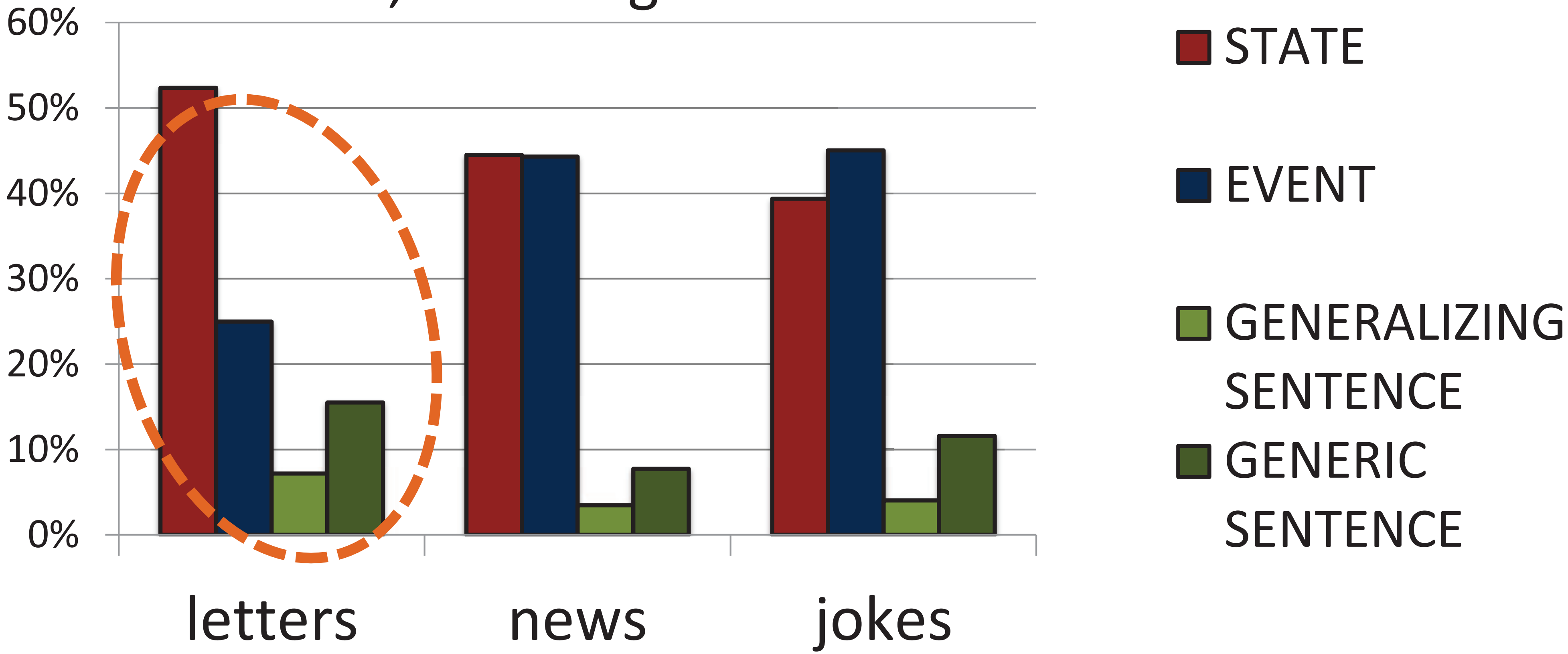

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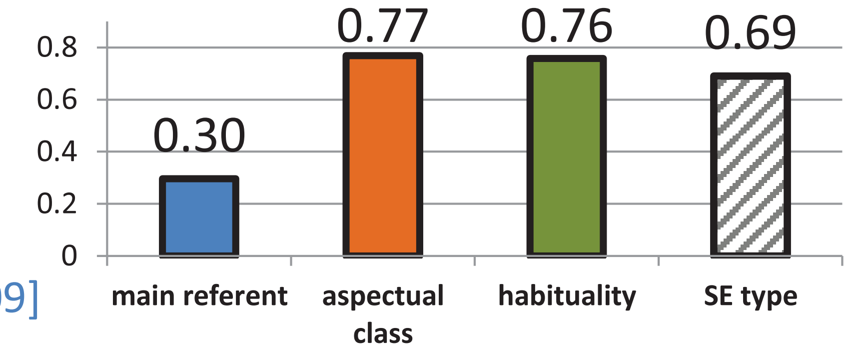
Summary:
annotation of situation entity types

- 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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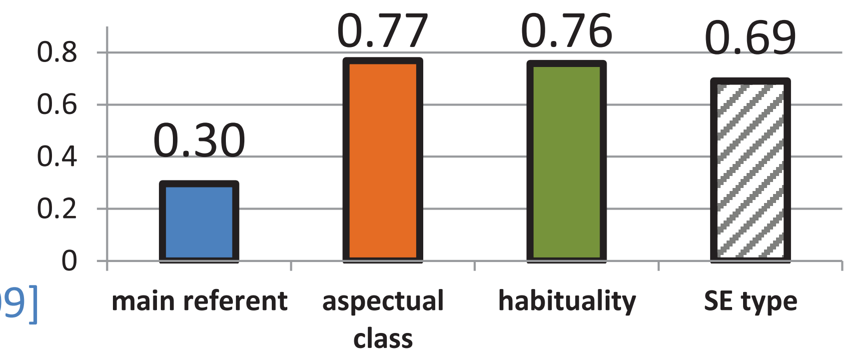
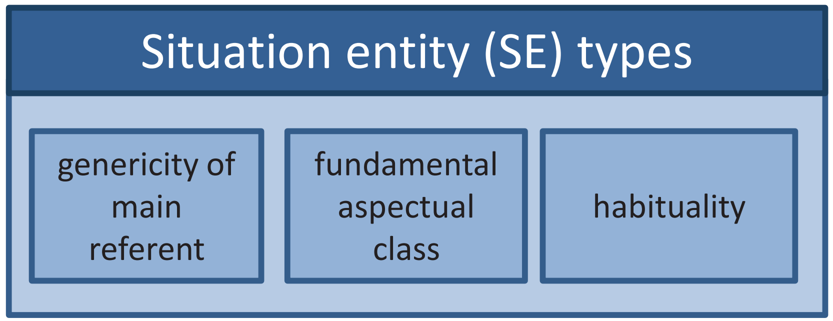
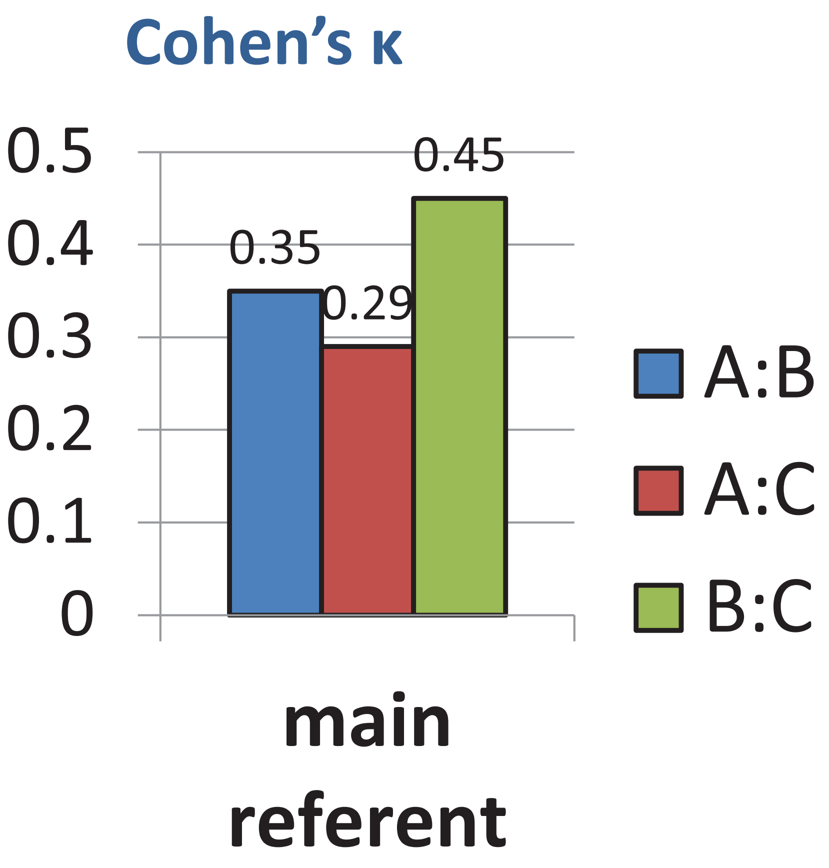


- Feature-based approach
  - helps annotators during annotation
  - analysis of disagreements
  - identify problems in guidelines
    → follow-up study on genericity



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



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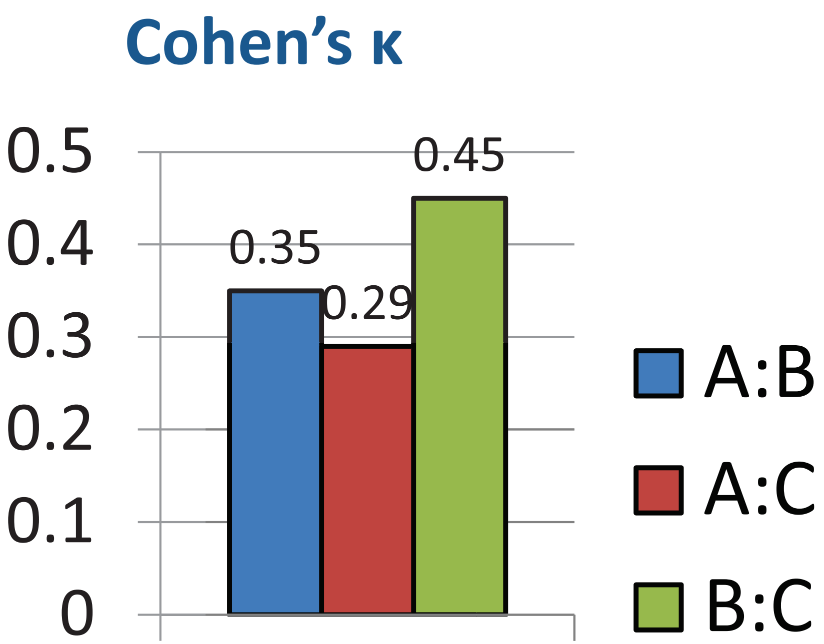

main referent

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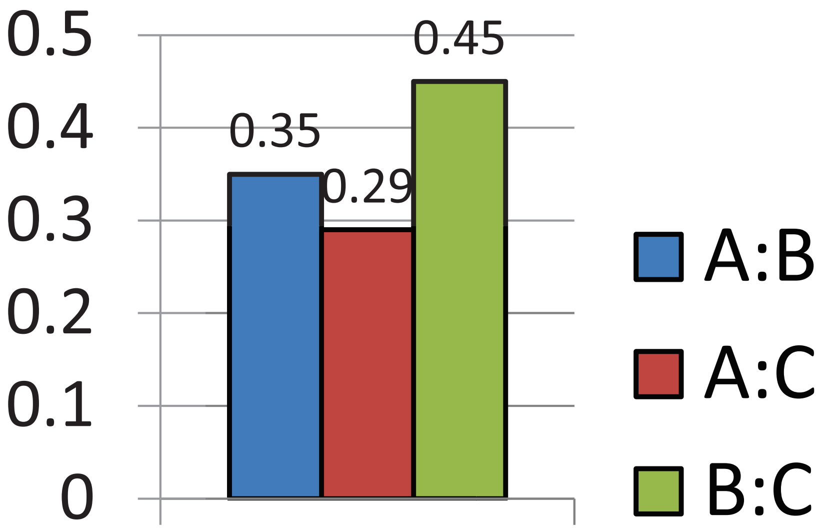
Cohen's κ



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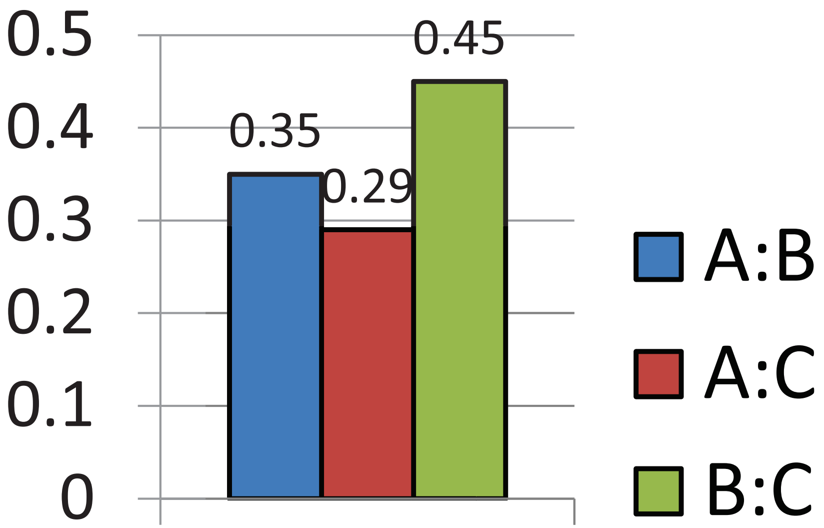

main referent

specific
generic
expletive

- **clarity** of annotation guidelines?
  - ***sparsity*** of label *generic*:

    B&C (κ = 0.45)
    - 2358 non-generic
    - 122 generic by one
    - 43 generic by both

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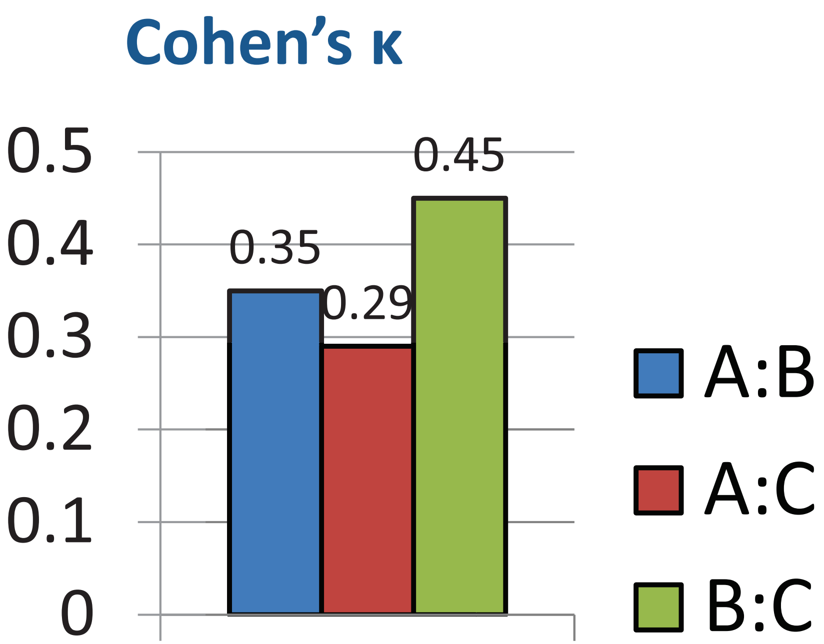

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  - ***sparsity*** of label *generic*:
    B&C (κ = 0.45)
    - 2358 non-generic
    - 122 generic by one
    - 43 generic by both
  - ***ambiguity / underspecification***
    ~ 30% of disagreements (estimate based on small qualitative analysis)
    every kid in New York
    "you" in letters

joint work with Melissa Peate Sorensen

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.

joint work with Melissa Peate Sorensen

Generics follow-up study

address the issue of ***clarity***:
compared definition to existing theories [Carlson & Pelletier 1995]
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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.

joint work with Melissa Peate Sorensen

Generics follow-up study

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

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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, ≈ 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 …*

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***The blobfish** is a deep sea fish of the family…*
***Blobfish** are typically shorter than 30cm.*

inductive

[Carlson 1995]

***American football** is a sport*
played by two teams of eleven players.
***The offense** attempts to advance an oval ball …*

rules and regulations

***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 …*

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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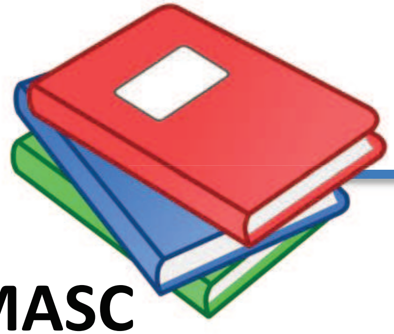
TODO: build computational model for detecting genericity of clauses

Overview



MASC

(automatic) segmentation

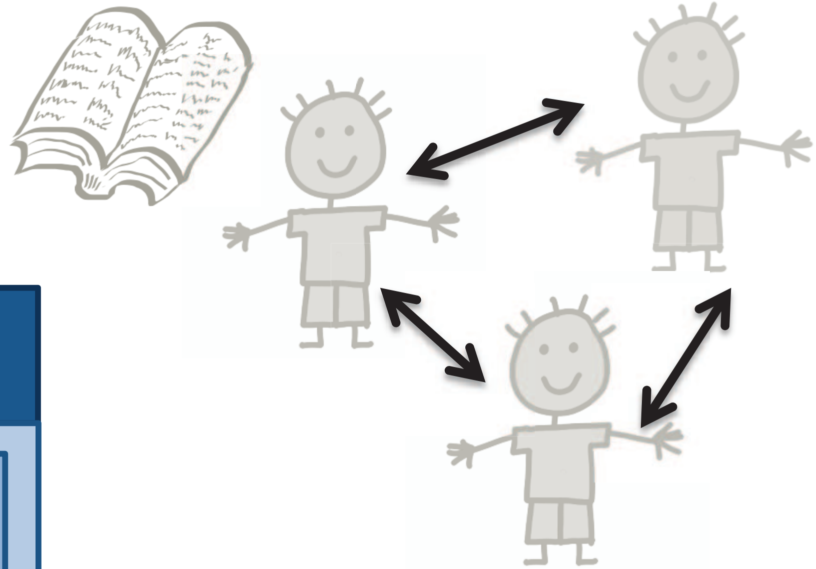
Situation entity (SE) types

genericity of main referent	fundamental aspectual class	habituality

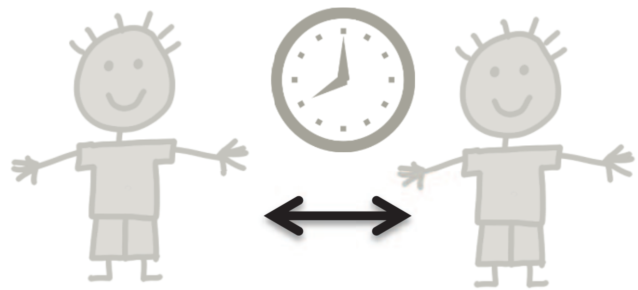
Feature-based annotation

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

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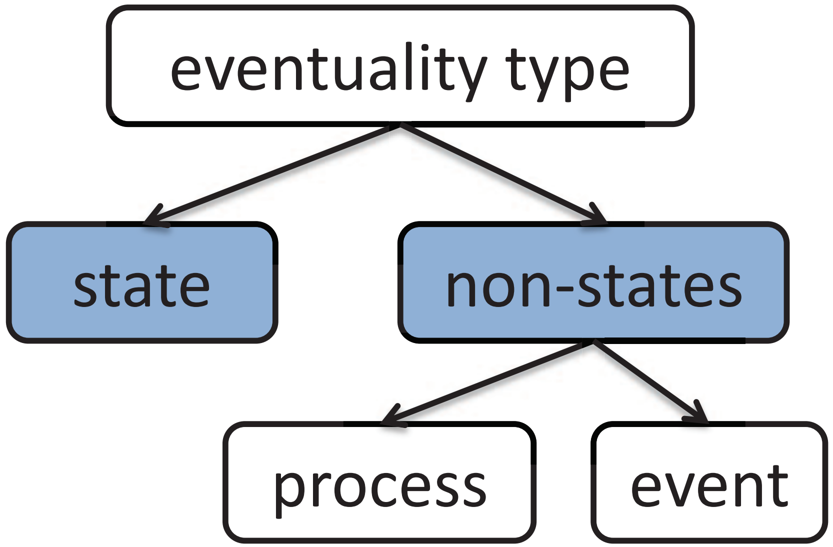
Bach (1986):

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)

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

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

*John will **love** this cake!*	*John love cake*	**stative**
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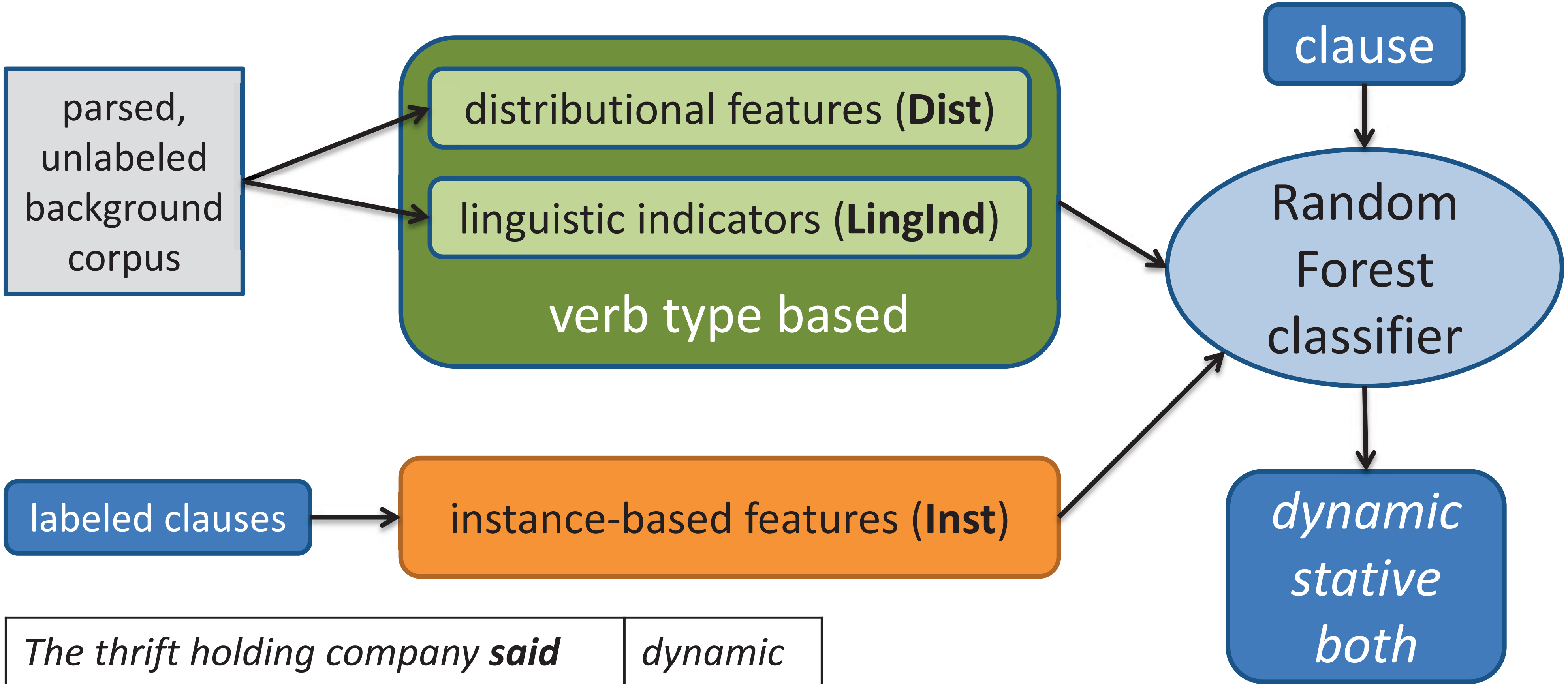
Method: Overview

- supervised three-way classification setting



*The thrift holding company **said***	*dynamic*
*it **expects** to obtain approval*	*stative*
*and **recognizes** the danger.*	*both*

Linguistic Indicators

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

parsed, unlabeled background corpus (GigaWord)

verb types

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

continuous adverb	*continually endlessly*
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manner adverb	*furiously patiently*
temporal adverb	*again finally*
in-PP	*in an hour*
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tense extraction: Loaiciga et al. (2004)

Linguistic Indicators

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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	*says*
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future	*will say*
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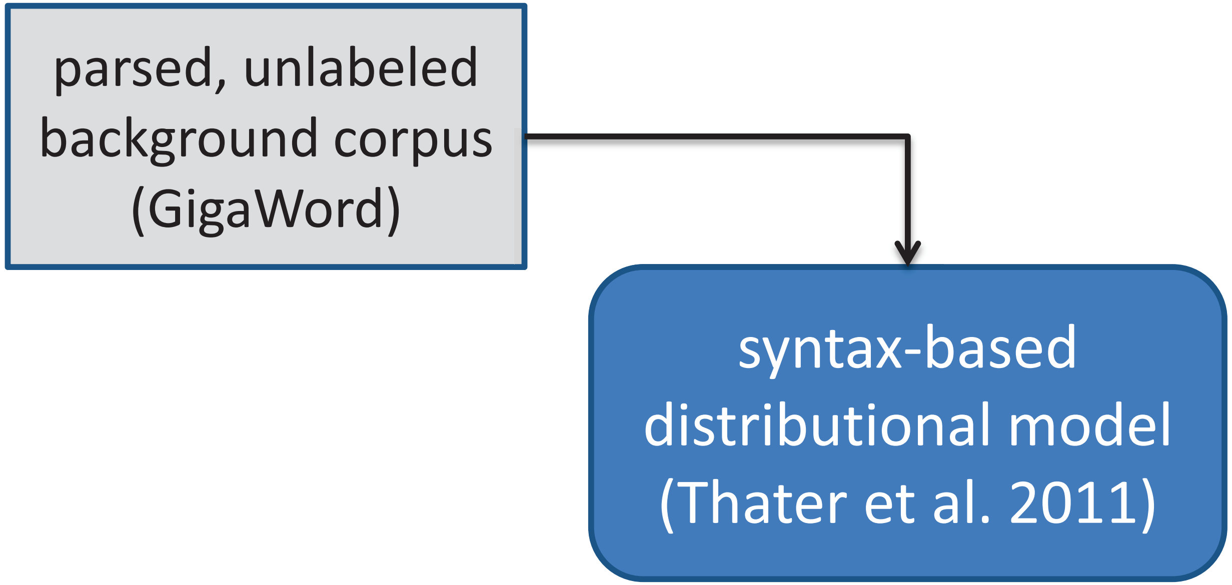
Distributional features

- average similarities with verbs in seed sets



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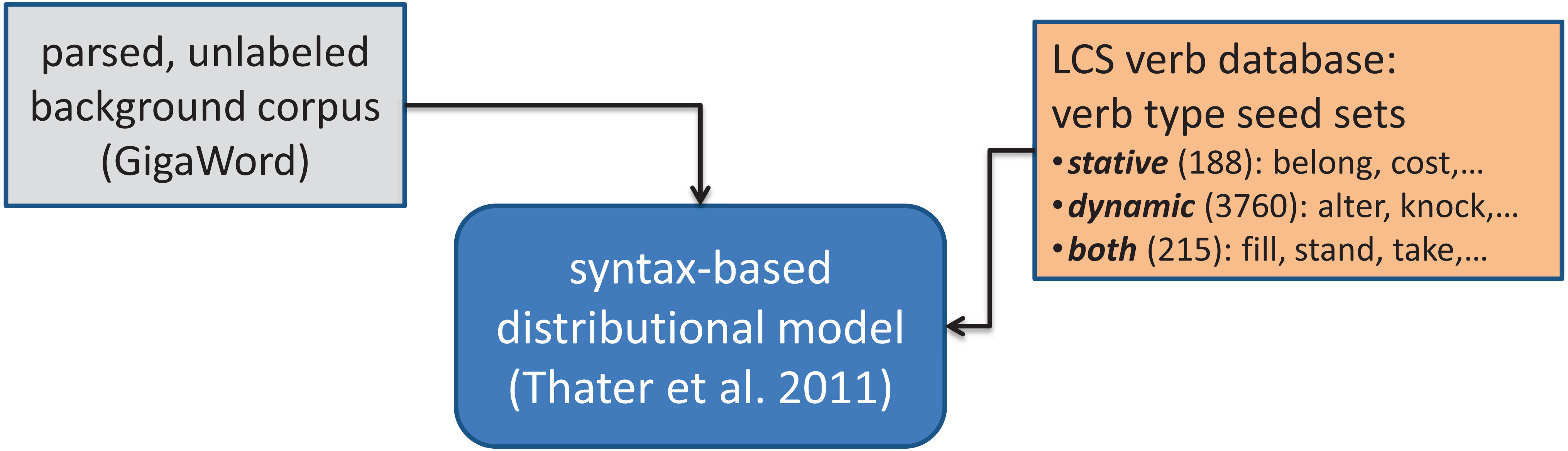

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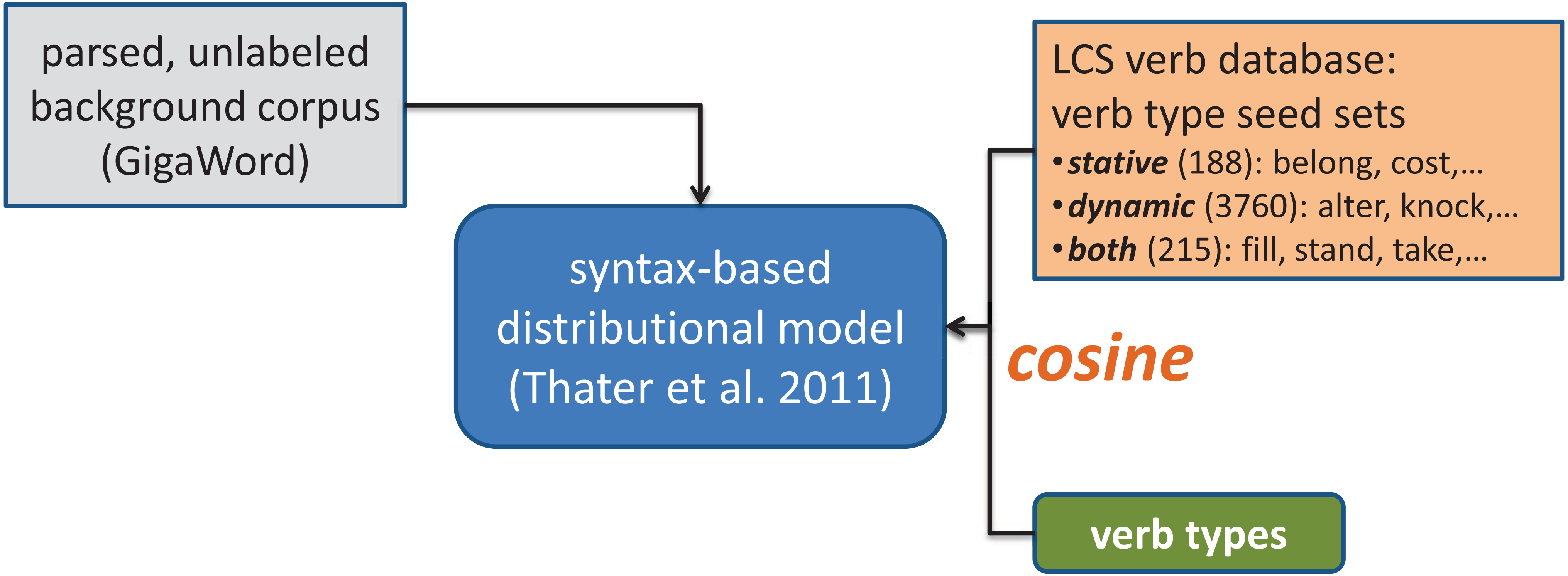

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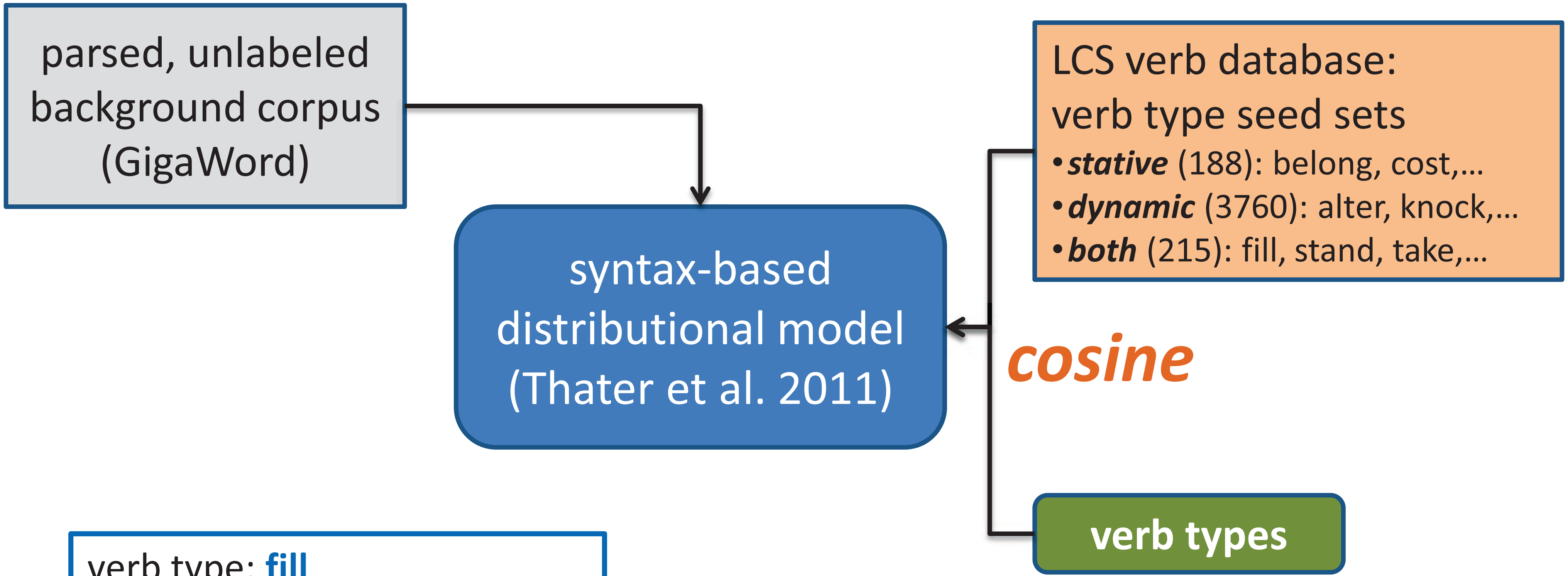

verb type: **fill**
avg. sim. with *stative*: 0.31
avg. sim. with *dynamic*: 0.27
avg. sim. with *both*: 0.16

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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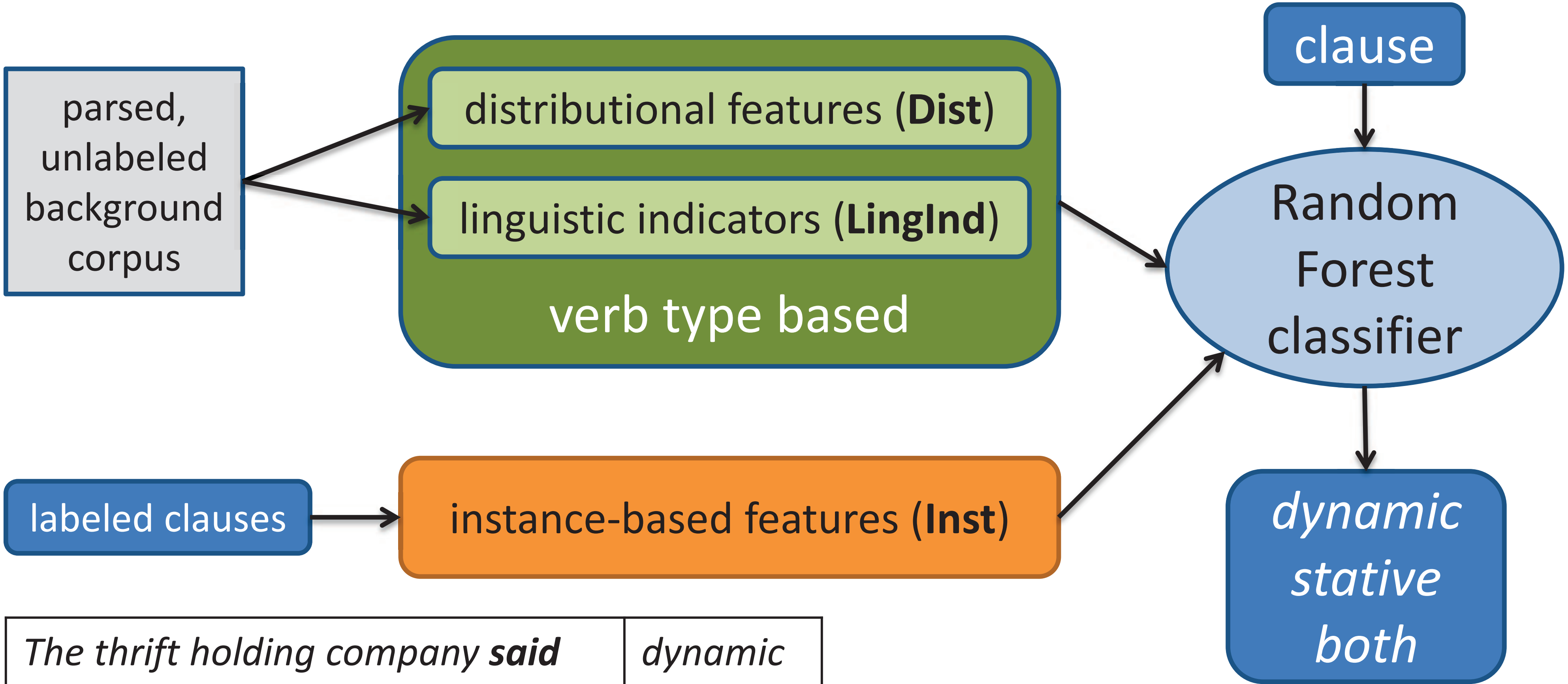

*The thrift holding company **said***	*dynamic*
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Experiments 1&2: SEEN vs. UNSEEN verbs

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

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SEEN verbs:

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Type-based features
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(= memorizing most frequent class per verb)

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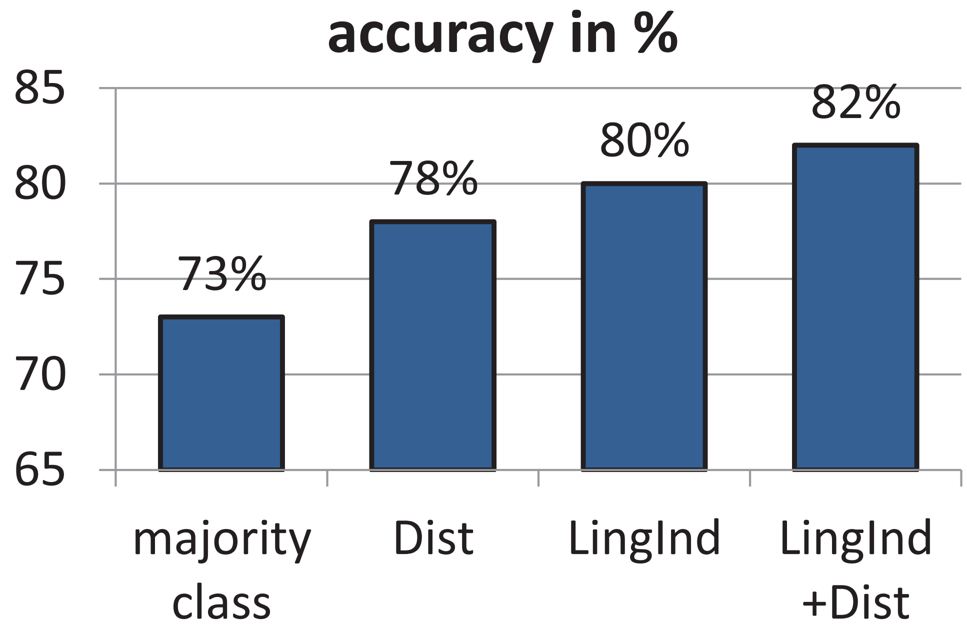

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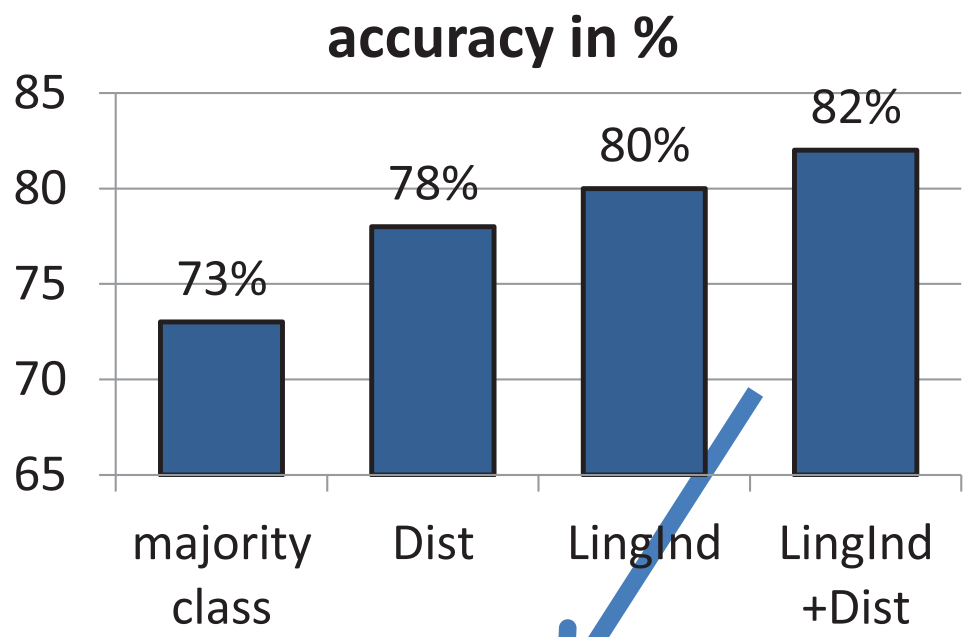
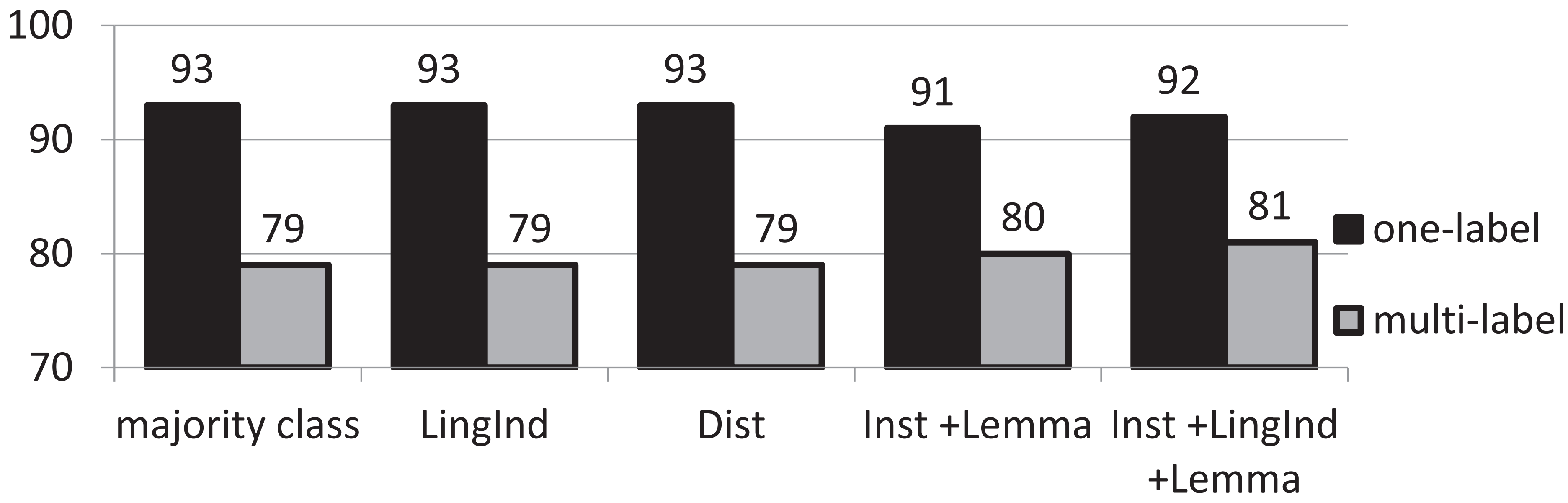


Type-based features generalize across verb types.

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

accuracy in %



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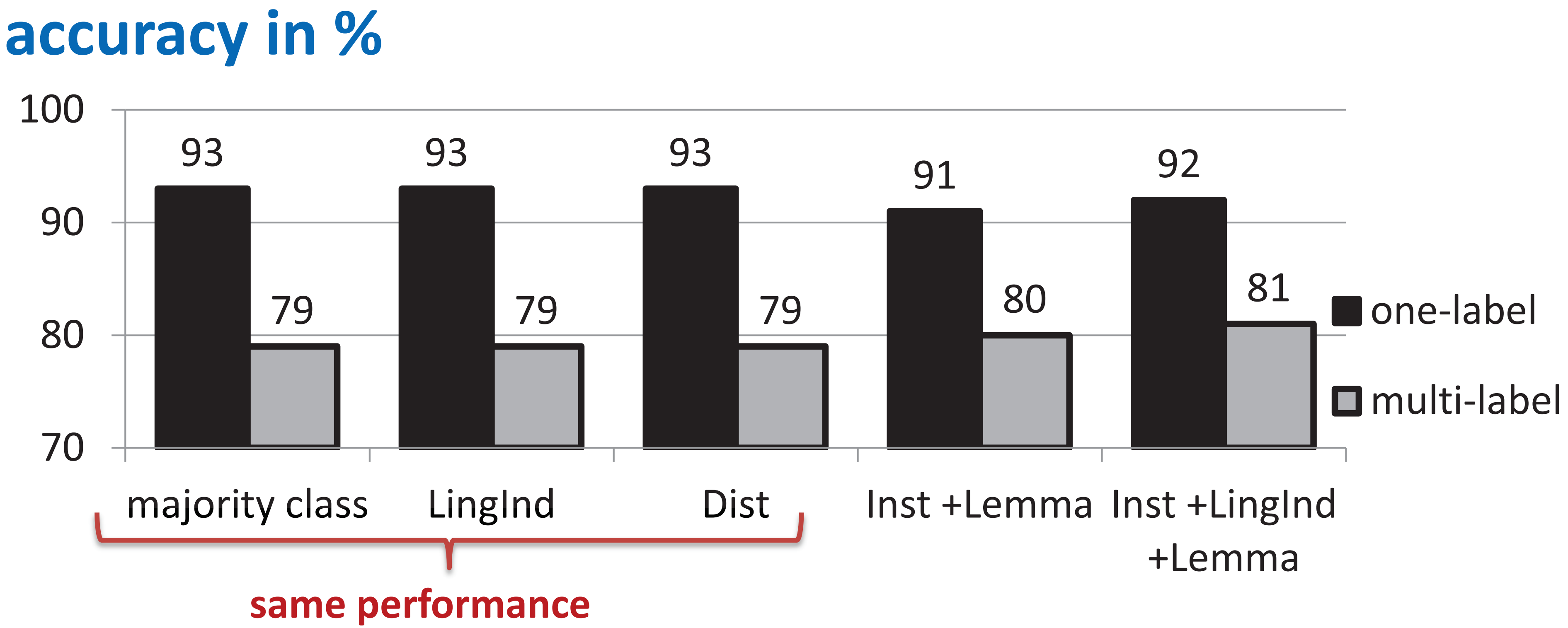

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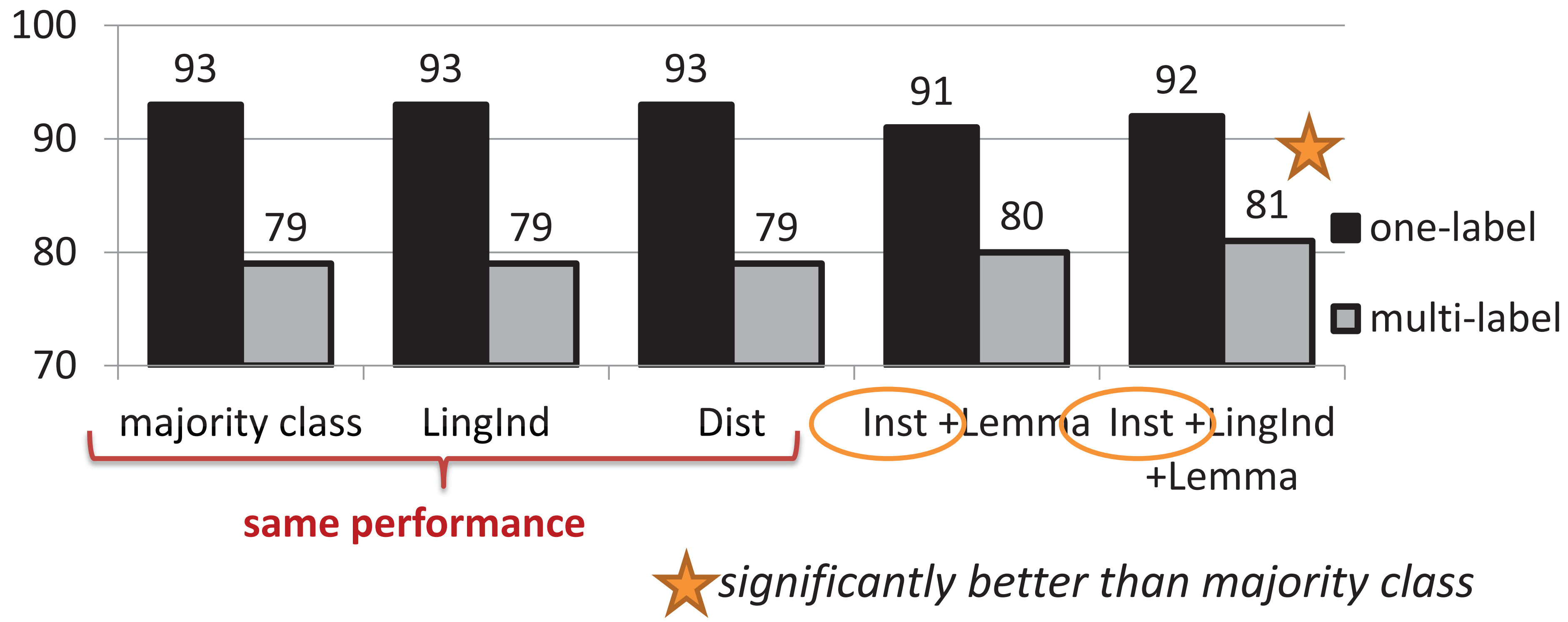

Instance-based features are essential for classifying ambiguous verbs.

Experiment 4: INSTANCE-BASED classification

Asp-Ambig:

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

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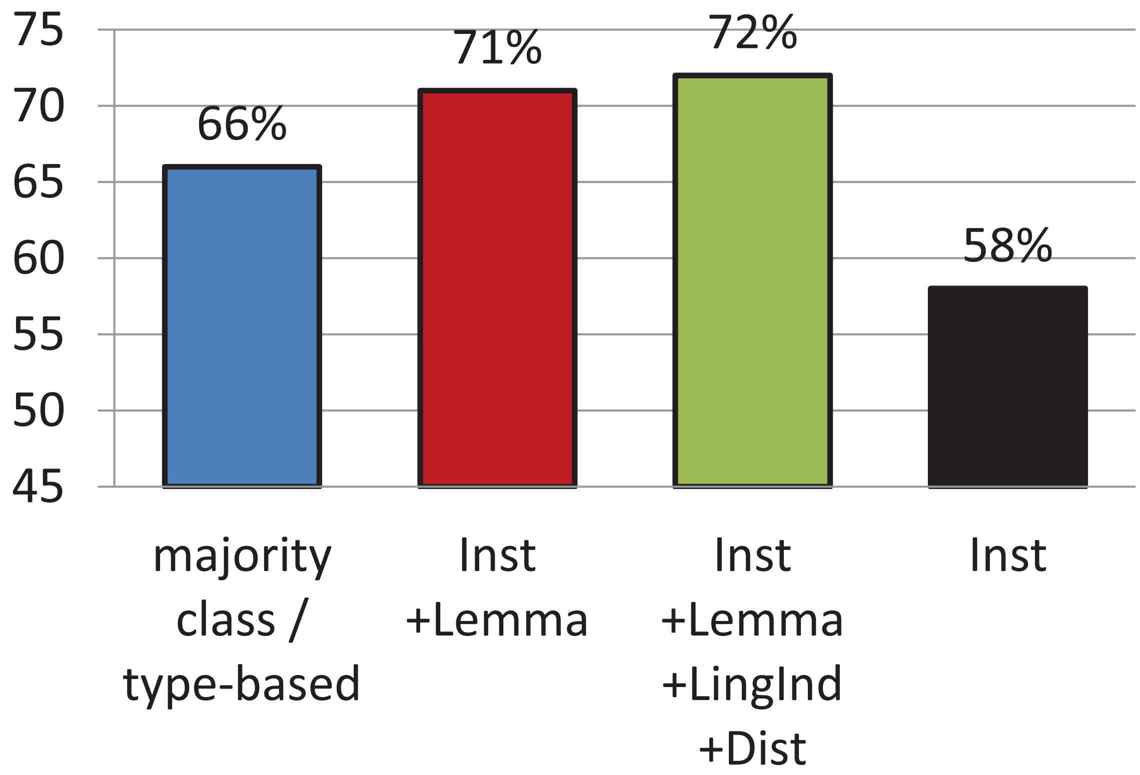
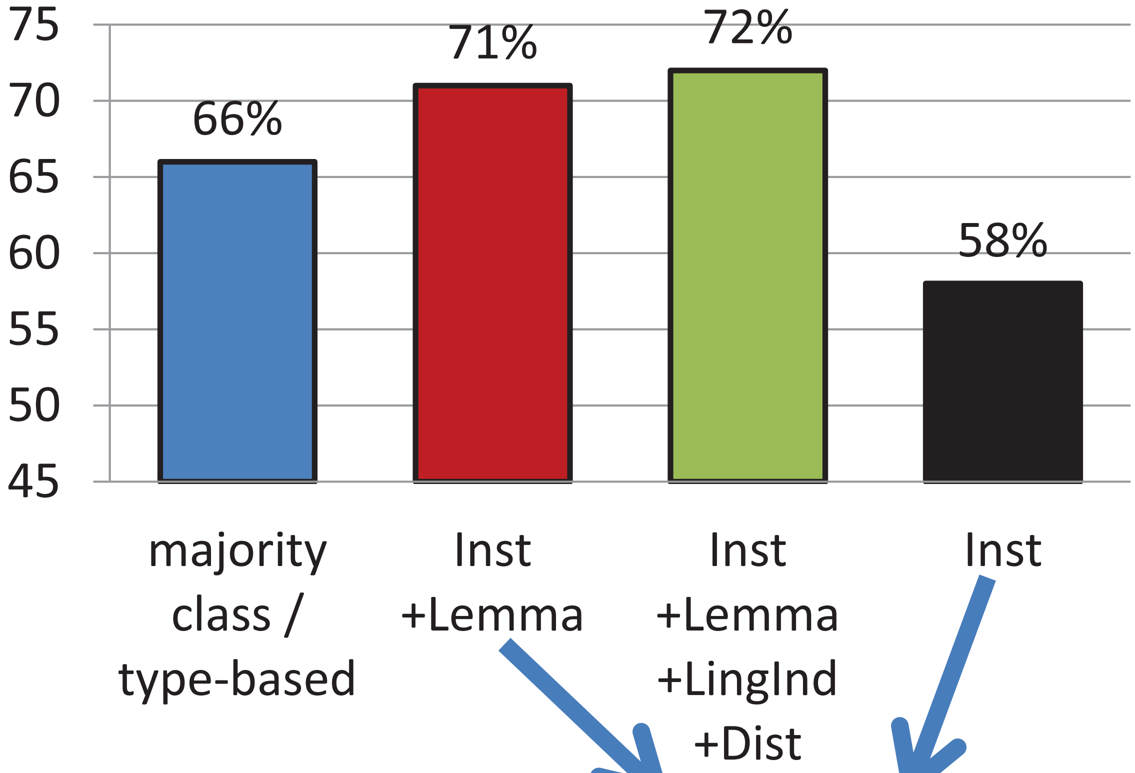
Asp-Ambig: micro-average accuracy



Experiment 4: INSTANCE-BASED classification

Asp-Ambig:
- 2667 sentences for 20 frequent ambiguous verbs (from Brown)
- 2 annotators, κ = 0.6

Asp-Ambig: micro-average accuracy



Instance-based features do not generalize across verb types.

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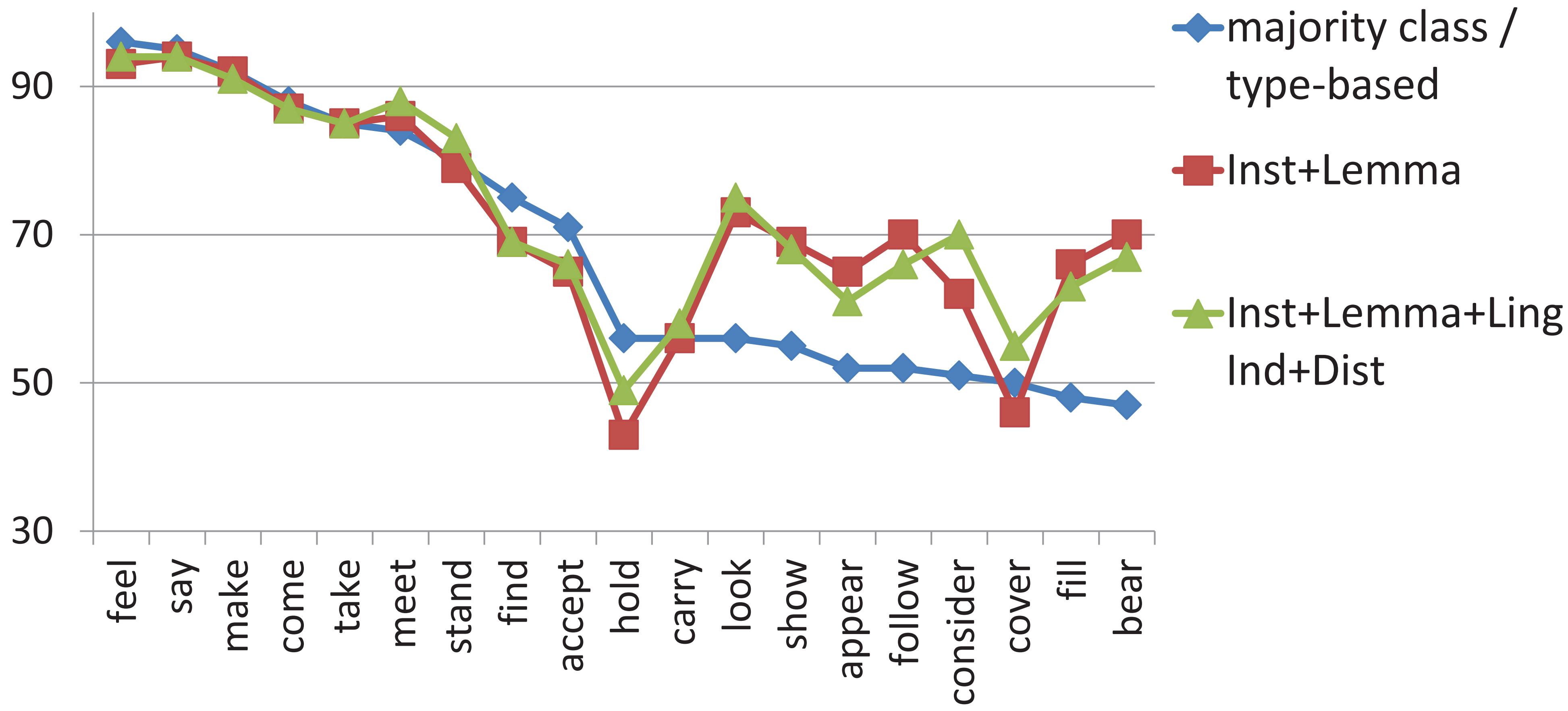

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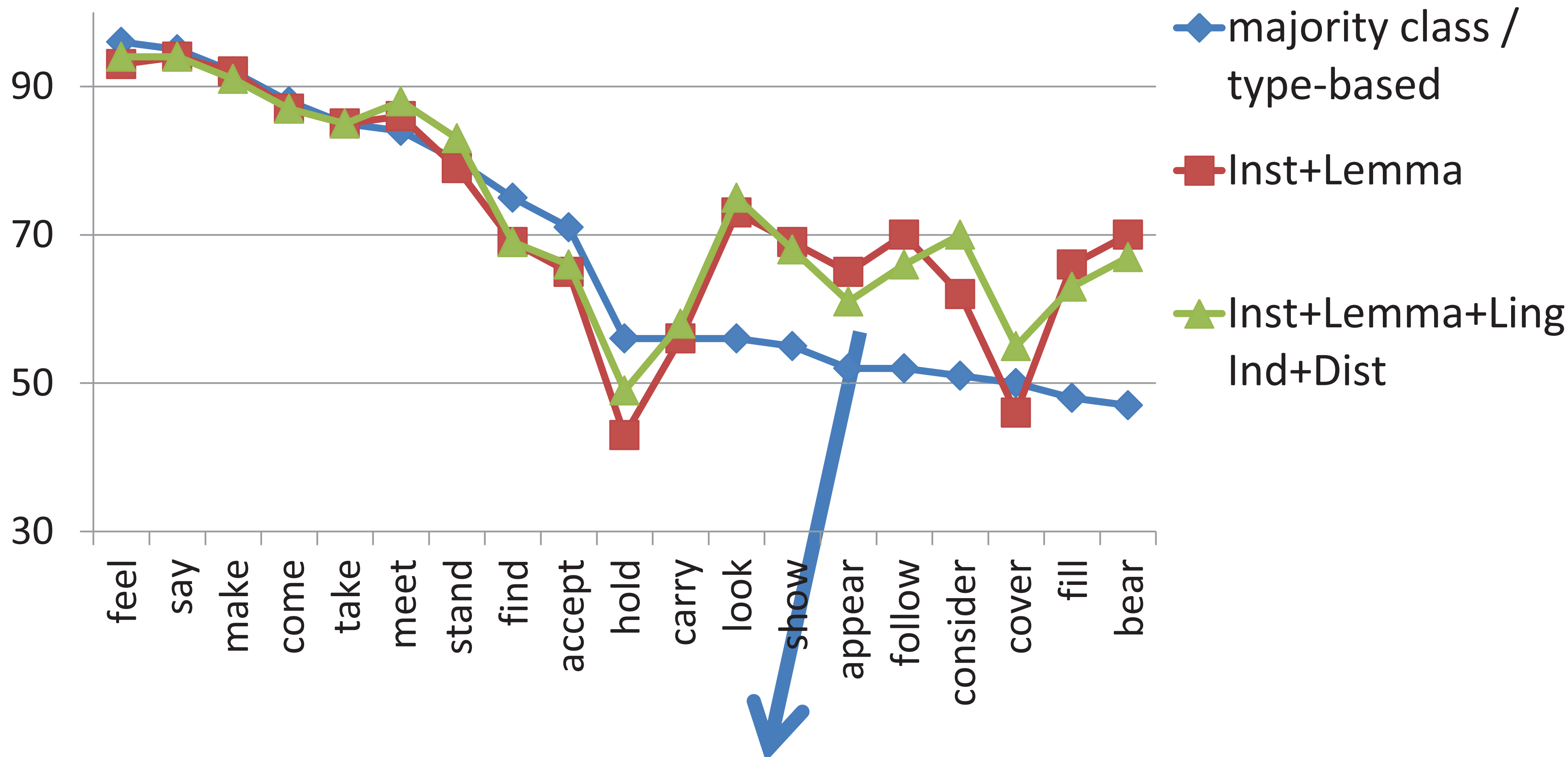

→ The more ambiguous the verb, the more essential are instance-based features.

→ 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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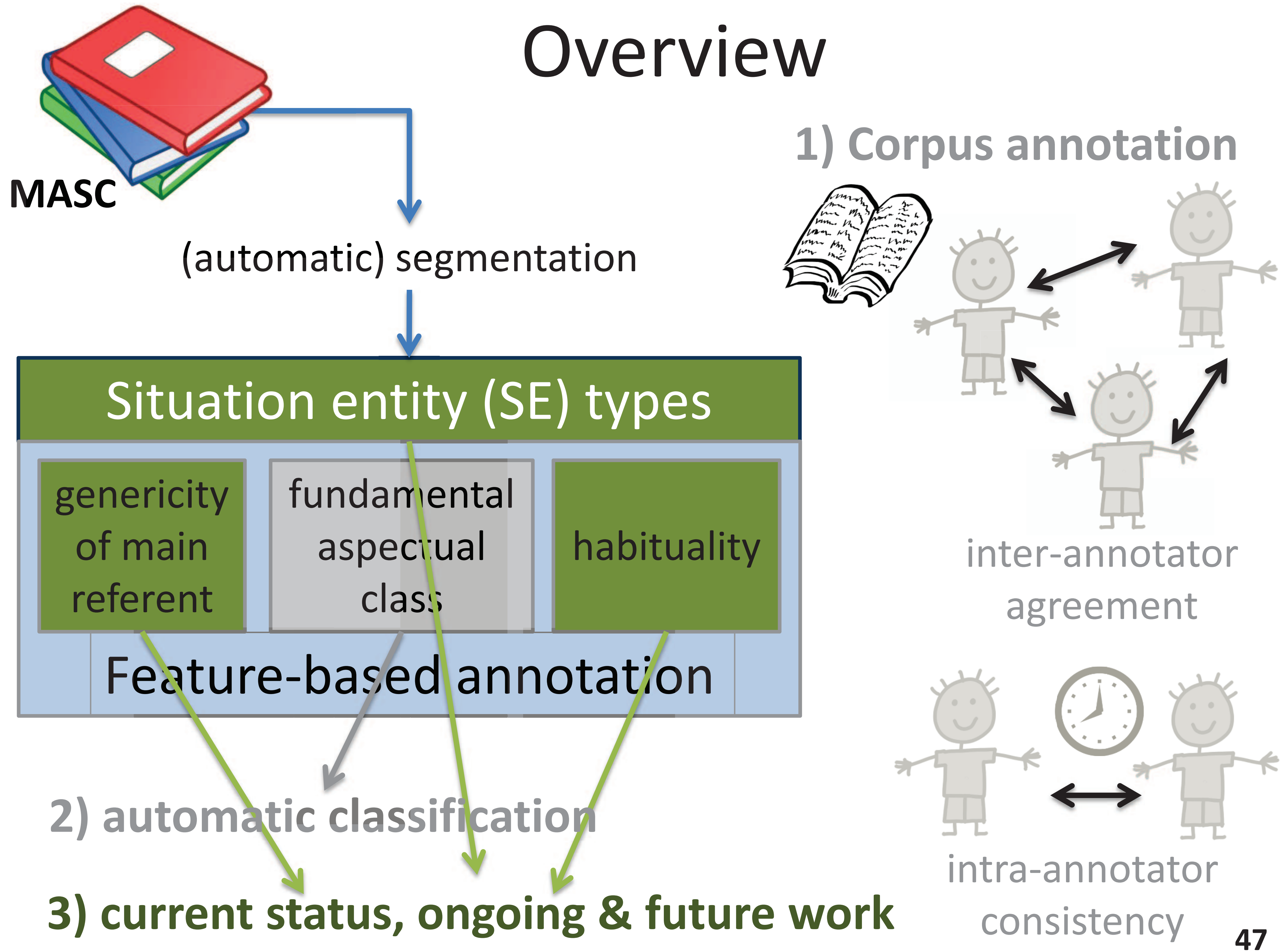
treat different verb types differently

⬇

globally well-performing system



Overview
MASC
(automatic) segmentation
Situation entity (SE) types
genericity of main referent
fundamental aspectual class
habituality
Feature-based annotation
1) Corpus annotation
inter-annotator agreement
intra-annotator consistency
2) automatic classification
3) current status, ongoing & future work

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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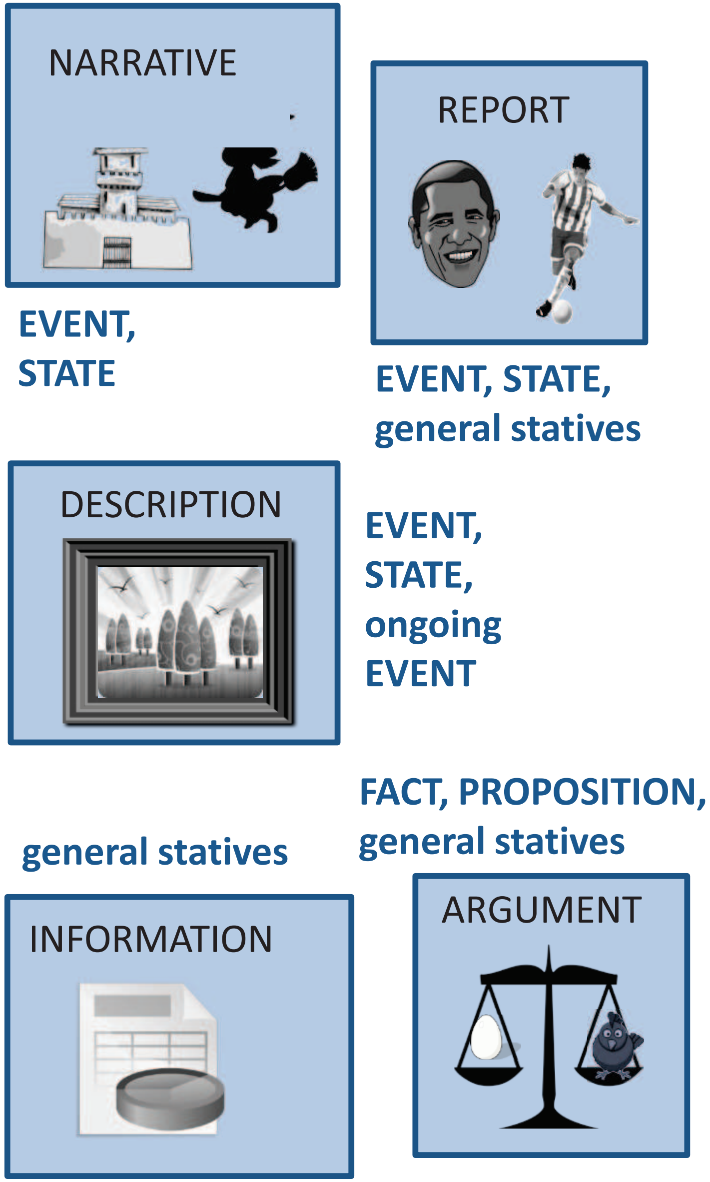
approach: combination of local features with discourse-based features

- extending upon Palmer et al. (2007)

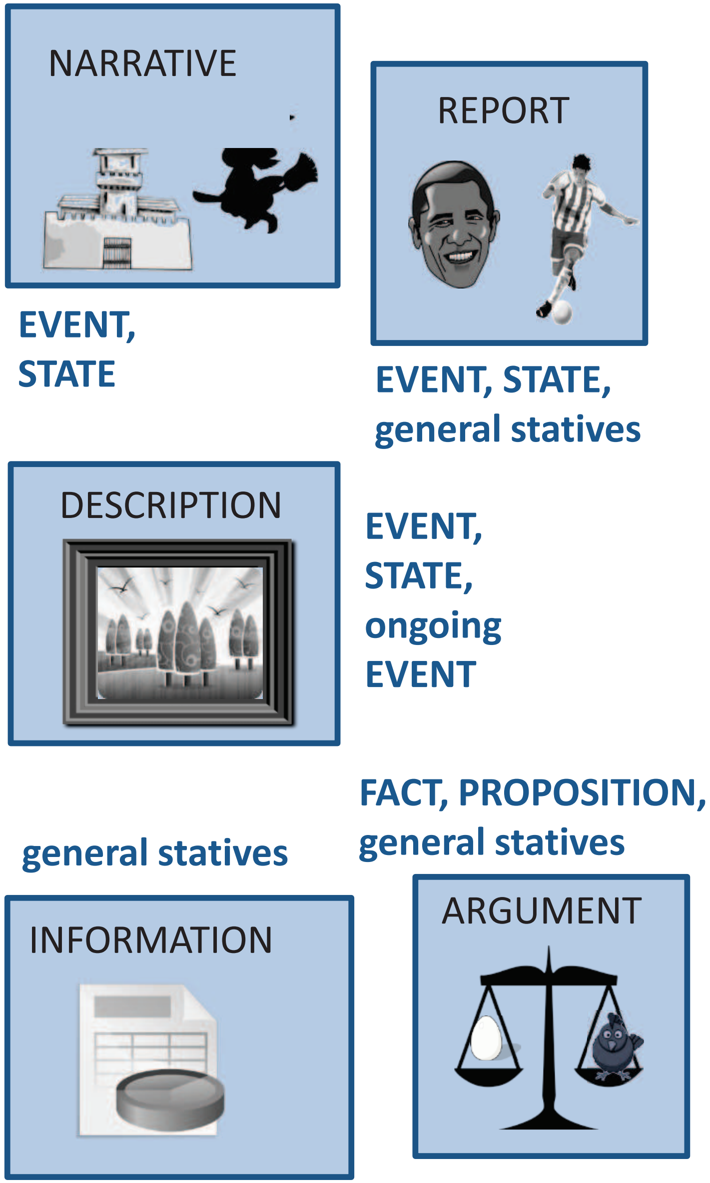
Relevance of discourse modes

[Smith 2003]



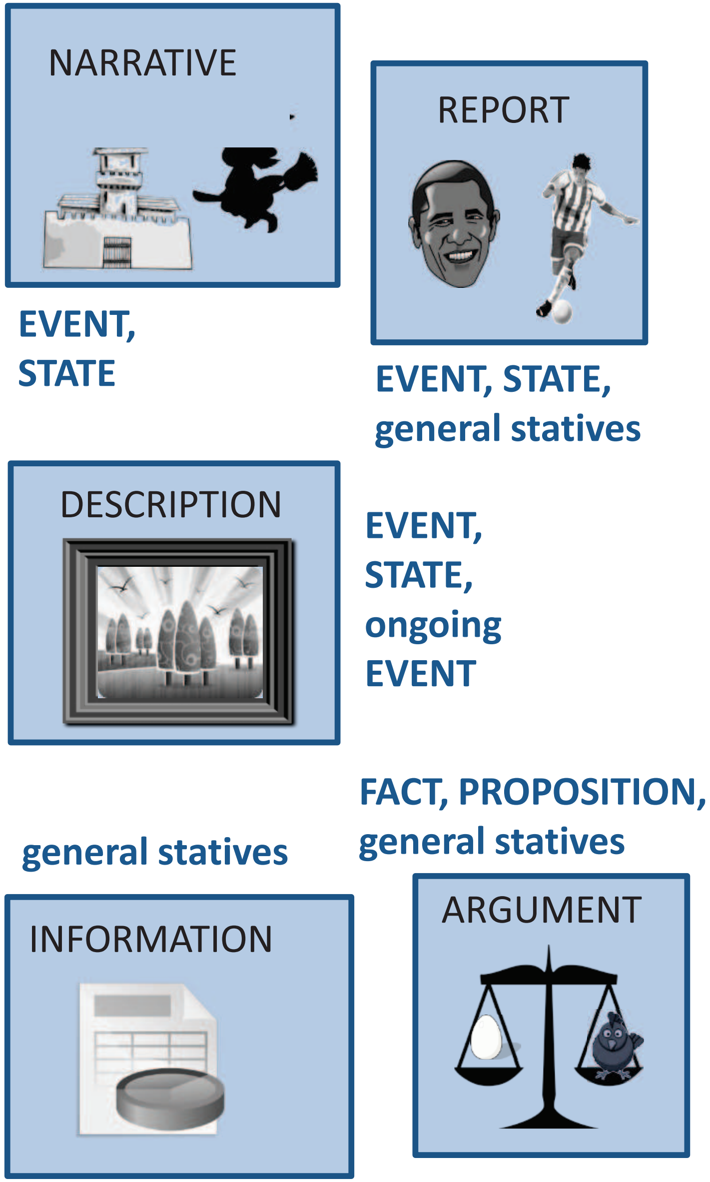
- **future work**: create **annotated corpus** for discourse modes

Relevance of discourse modes
[Smith 2003]



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

Relevance of discourse modes
[Smith 2003]



- **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 & ambigous 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

situation entity types
aspectual information
how speaker/writer presents a situation

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MT evaluation

Can we use SE type information for evaluating translation quality? (start with related languages)

Future / ongoing work

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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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