Detecting Relational Constructions in German Texts Automatically

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concept types

person, pope, house, verb, sun, Mary, wood, brother, mother, meaning, distance, spouse, argument, entrance

concept types: relationality ($\pm R$)

non-relational ($-R$)	person, pope, house, verb, sun, Mary, wood
relational ($+R$)	brother, mother, meaning, distance, spouse, argument, entrance

Löbner (2011)

concept types: uniqueness of reference ($\pm U$)

	non-unique reference ($-U$)	unique reference ($+U$)
non-relational ($-R$)	person, house, verb, wood	Mary, pope, sun
relational ($+R$)	brother, argument, entrance	mother, meaning, distance, spouse

Löbner (2011)

Concept types

	non-unique reference	unique reference
non-relational ($-R$)	**sortal concept** person, house, verb, wood $\lambda x.\ P(x)$	**individual concept** Mary, pope, sun $\iota u.\ P(u)$
relational ($+R$)	**proper relational concept** brother, argument, entrance $\lambda y \lambda x.\ R(x, y)$	**functional concept** mother, meaning, distance, spouse entrance $\lambda y.\ f(y)$

Löbner (2011)

Concept types and determination (Löbner 2011)

Theory of concept types and determination (CTD)

Every concept type comes with a ‘natural mode’ of determination: congruent determination.

DET_{-U}:	indefinite	a book, ↱ a pope
	plural	books, ↱ popes
	quantifiers	any book, ↱ any pope
	demonstratives	this book, ↱ this pope
DET_{+U}:	singular definite	the pope, ↱ the stone
DET_{-R}:	absolute	the pope , ↱ the head
DET_{-R}:	possessive pronoun	my head, ↱ my stone

Incongruent determination: shifts

- The teacher has recommended a book. Mary buys the book.
  (anaphoric use)
- Mothers act like popes.
  (generic uses)
- Mary bought a Picasso.
  (metaphorical shift)

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Incongruent determination is made explicit in languages with:

- weak/strong definite article split

  e.g. Rhineland dialects, ‘Dr Zoch kütt’ vs. ‘Dä Zoch kütt’
- (in)alienability split

  e.g. Lakhota, 2SG-spirit DEF ‘your spirit’ vs. 2SG-REL-book DEF ‘your book’

Research hypothesis

C02: Conceptual shifts – statistical evidence

- Congruent determination is more frequent than incongruent determination.
- The frequency pattern of determination modes in which a noun occurs (its determination fingerprint) depends on its concept type.

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Question

Is it possible to determine the concept type of a noun automatically?

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Question

Is it possible to determine the concept type of a noun automatically?

Necessary prerequisite

Determine the determination mode automatically:

- relatively easy for $Det_{\pm U}$ (closed class of determiners)
- more complex for $Det_{\pm R}$ (topic of today's talk)

Aim: automatic detection of relational constructions in German

4 basic constructions:

- [Der Hut]$_{P'um}$ [des Mannes]$_{P'or}$ ist grün. (right genitive, *rgen*)
- [Maries]$_{P'or}$ [Hut]$_{P'um}$ ist grün. (left genitive, *lgen*)
- [Mein]$_{P'or}$ [Hut]$_{P'um}$ ist grün. (possessive pronoun, *lpron*)
- [Der Hut]$_{P'um}$ [von Marie]$_{P'or}$ ist grün. (right ‘von’, *rvon*)

non-trivial task:

Aim: automatic detection of relational constructions in German

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non-trivial task:

- Er soll den Knochen vom Hund aufheben. (noun attached PP)
- Er soll den Knochen vom Boden aufheben. (verb attached PP)
- Peter bekommt ein Buch von Marie. (ambigue)

Data

- Seed corpus containing 300 sentences (Horn & Kimm 2014)
- main data: 800 sentences (randomly drawn from Leipzig Corpora) annotated by 2 annotators with 'PUM', 'POR' and no-poss
- example: (Der, PUM.rvon) (Bürgermeister, PUM.rvon) (von, POR.rvon) (Berlin, POR.rvon) (spricht, no-poss) (schnell, no-poss)
- annotator agreement: 81.9% ($\kappa = 0.767$, max $\kappa = 0.936$)

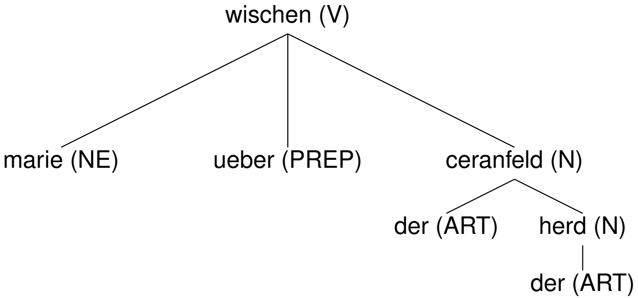
Data

Type	Frequency
no relation (*no-poss*)	4915
Right genitive (*rgen*)	180
Possessive pronoun (*lpron*)	120
Right '*von*' (*rvon*)	13
Left genitive (*lgen*)	12

frequencies of possessive classes in seed corpus; word-based count

Features: extracted from MATE trees

Marie wischte über das Ceranfeld des Herdes.



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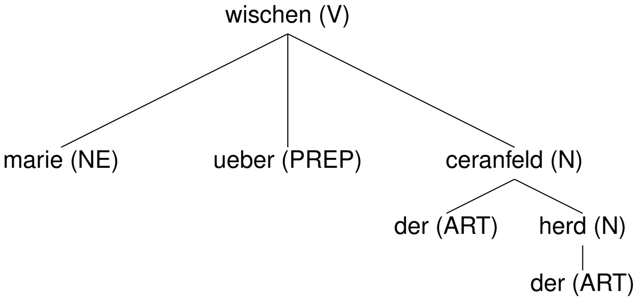


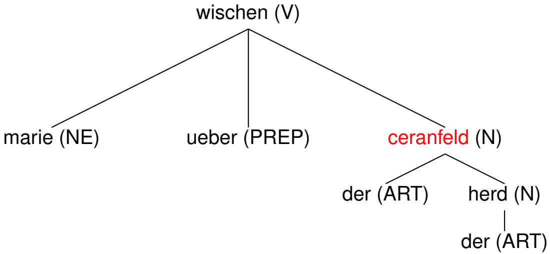
For each word take 5-tuple:

surface form	Ceranfeld
lemma	Ceranfeld
POS tag	N
case marker	acc
s-ending	false

Features: multidimensional feature vector

syntactic parent + context window: ± 2

x_{i-2}	x_{i-1}	x_i	x_{i+1}	x_{i+2}	$x_{p_i}^{?}$
über	das	Ceranfeld	des	Herdes	wischte
über	der	ceranfeld	der	herd	wischen
PREP	ART	N	ART	N	V
-	acc	acc	gen	gen	-
false	true	false	true	true	false



Marie wischte über das Ceranfeld des Herdes.

Tree classifier

Rule base

- $rvon \equiv \mathrm{N} \leftarrow \mathrm{von} \leftarrow (\mathrm{N} \vee \mathrm{NE})$
- $lpron \equiv \mathrm{N} \leftarrow \mathrm{PRPOSS}$
- $rgen \equiv \mathrm{N} \leftarrow \mathrm{N} \leftarrow \mathrm{ART}$[1]
- $lgen \equiv \mathrm{N} \leftarrow \mathrm{NE}_{\mathrm{gen}}$
  $lgen \equiv \mathrm{N} \leftarrow \mathrm{N}_{\mathrm{gen}}$ very rarely
  $\Rightarrow \mathrm{N}_{\mathrm{gen}}$ many misclassifications.

[1] Original rule: $rgen \equiv \mathrm{N} \leftarrow \mathrm{N}_{\mathrm{gen}} \leftarrow \mathrm{ART}$

Statistical ML algorithms

Statistical Algorithms

- **Non-sequential**: Maximum Entropy[2]
- **Sequential**: Conditional Random Fields[3], SVM^{HMM}[4]

[2] Ratnaparkhi (1998); implementation: OpenNLP

[3] Lafferty (2001); implementation: http://www.chokkan.org/software/crfsuite/

[4] Altun (2003); implementation: http://www.cs.cornell.edu/people/tj/svm_light/svm_hmm.html

Word-based evaluation by classifier

	SVM^{HMM}		CRF		ME		Tree	
	P	R	P	R	P	R	P	R
no-poss	97.8	99.3	97.3	99.2	95.0	**99.7**	**98.3**	95.2
POSS	90.8	79.6	88.5	75.3	**91.9**	50.8	66.7	**82.2**
PUM	91.4	75.5	91.9	70.5	**94.8**	52.2	55.1	**76.3**

30-fold cross-validation, green: Highest F-value in a row

Problems with the tree classifier: “... sei seine Partei$_{PUM}$ der Auffassung$_{POSS}$, ...”

Word-based evaluation by classifier and relational type

		SVM^{HMM}		CRF		ME		Tree	
		P	R	P	R	P	R	P	R
lgen	POSS	93.15	**71.58**	**94.83**	57.89	93.48	45.26	83.12	67.37
lgen	PUM	97.5	**53.42**	97.22	47.95	**100**	28.77	84.21	43.84
lpron	POSS	96.51	**92.74**	**96.93**	88.27	99.3	78.77	92.31	87.15
lpron	PUM	**99.49**	81.07	99.47	77.37	98.18	66.67	96.76	**86.01**
rgen	POSS	99.25	**83.17**	**99.37**	78.64	99.12	56.28	96.62	82.66
rgen	PUM	96.75	**78.63**	96.54	73.61	**97.66**	55.15	89.7	78.1
rvon	POSS	**98.4**	58.57	96.9	59.52	94.74	8.57	95.6	**82.86**
rvon	PUM	94.23	63.64	**95.45**	54.55	91.67	14.29	94.55	**67.53**

Problematic cases:

- *lgen*: “Peters Haus” (NE)
- *rvon*: “das Haus von Peter” vs. “Maria hat das Buch von Peter bekommen”
- *rgen*: “die Wut der Arbeiter” (nom.? gen.?)

Results of merging decisions: majority vote

Type	P	R	F
POSS	91.6	80.3	85.6
PUM	93.2	74.4	82.7

Structure-based evaluation

	P	R	F
Full matches	93.58	87.14	90.24
Partial matches	94.38	88.64	91.42

Examples:

- **Gold**: das Haus$_{\text{PUM}}$ von Peter und Maria$_{\text{POSS}}$
- **Silver**: das Haus$_{\text{PUM}}$ von Peter$_{\text{POSS}}$ und Maria

The influence of chunk lengths

	P	R	F	Total
long chunks ($LR > 4$)	97.7%	71.7%	82.7%	61
short chunks ($LR \leq 4$)	94.1%	90.4%	92.2%	597

Summary

Next steps:

- Merging parse trees
- Meta-learning
- Large-scale evaluation of Löbner's theory