

Canonicalization techniques for computer-mediated communication

Bryan Jurish,¹ Kay-Michael Würzner,² Maria Ermakova,¹ Sophie Arana¹
{jurish,wuerzner,ermakova}@bbaw.de

(1) Berlin-Brandenburgische Akademie der Wissenschaften

(2) Universität Potsdam

GSCL-2013 Workshop “*Verarbeitung . . . internetbasierter Kommunikation*”
Darmstadt, 23rd September 2013

The Big Picture

- The Situation
- The Problem
- The Approach

Canonicalization Methods

- Type-wise Conflation
 - ▶ Transliteration, Phonetization, Rewrite Cascade
- Token-wise Disambiguation
 - ▶ Dynamic Hidden Markov Model
- Problems & Workarounds
 - ▶ Lexical, Morphological, Phonological, Suprasegmental

Summary & Outlook

— The Big Picture —

Deutsches Textarchiv (DTA)

Primary Goals

- digitize ~ 1,300 print volumes, printed ~ 1600-1900
 - ▶ first editions of respective works
 - ▶ detailed metadata, highly accurate transcriptions
- TEI-XML corpus encoding & storage
 - ▶ DTA base format (DTABf) dialect
- linguistic analysis (automated)
 - ▶ tokenization, normalization, PoS-tagging, lemmatization
- online search (DDC) <http://www.ddc-concordance.org>
 - ▶ lemma-based, PoS-sensitive, spelling-tolerant

In Numbers

(DTA+DTAE 2013-05-02)

1,276 transcribed works

353,245 digitized pages

567,200,587 unicode characters

81,049,777 tokens (alpha-numeric)

1,947,414 types (alpha-numeric)

TODO: UPDATE FOR IBK CORPUS

The Situation

CMC Text Orthographic Conventions

- also applies to historical text, OCR output, ...
- many non-standard graphemic forms

nicht nciht, nert, net, nich, nicha,
“not” niiiiiiicht, nit, nnicht, ...

tschüss schüssi, tschaui, tschö,
“bye” tschöööö, tschüssi, tschüssie,
 tschüüüüüüüüüüsssss, ...

Conventional NLP Tools Strict Orthography

- IR systems, PoS taggers, stemmers, lemmatizers, morphological analyzers, parsers, ...
- Fixed lexicon keyed by (ortho)graphic form
- Conventional lexemes only (\approx newspaper domain)

The Problem

Conventional Tools
Unconventional Corpus

=

Soup

- Corpus variants *missing* from application lexicon
 - ▶ ***low coverage*** (many unknown types)
 - ▶ ***poor recall*** (relevant data not retrieved)
 - ▶ ***spurious “noise”*** (poor model fit)
 - ▶ ***... and more!***

The Approach: Canonicalization

a.k.a. (orthographic) ‘standardization’, ‘normalization’, ...



In a Nutshell

- *Map* each **word** w to a unique **canonical cognate** \tilde{w}
- *Defer* application analysis to canonical forms
- DTA::CAB infrastructure developed for historical text

Canonical Cognates

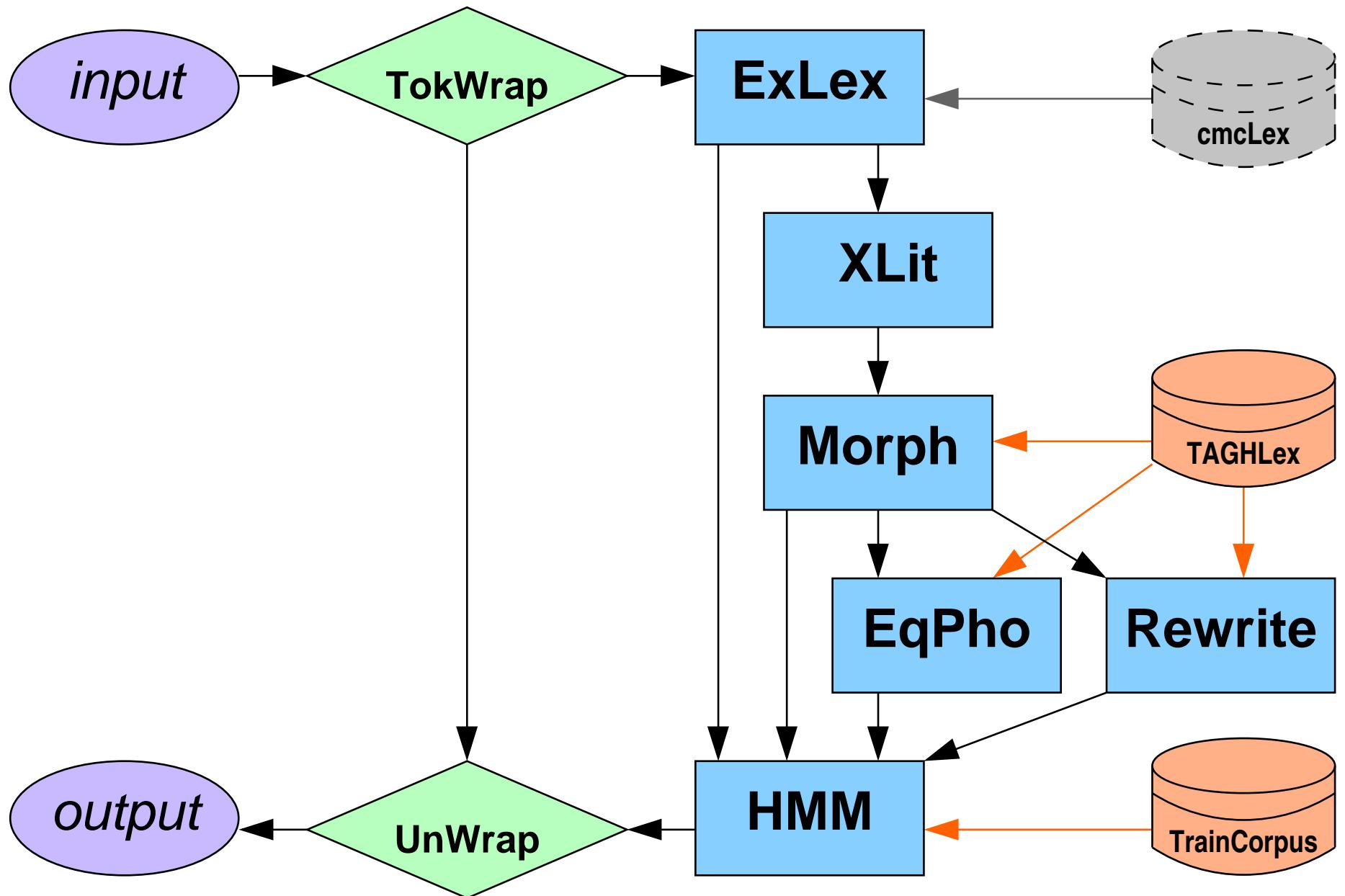
- Lexically active **conventional equivalent(s)** $\tilde{w} \in \text{Lex}$
- Preserve both **root** and **relevant features** of input

Conflation Relation \sim_r

- *Binary relation* on strings (words) in \mathcal{A}^*
- Prototypically a true *equivalence relation*

— Canonicalization Methods —

DTA::CAB System Architecture



Deterministic Transliteration (xlit)

Sketch

$$w \sim_{\text{xlit}} v : \Leftrightarrow \text{xlit}^*(w) = \text{xlit}^*(v)$$

- **Idea:** handle *non-standard characters* (*Jurish 2008, 2010b,c*)
- **Implementation:** $\mathcal{O}(1)$ character lookup table
- useful as *preprocessor* for subsequent methods

Examples

Foreign Scripts

北京 → BeiJing
Πλάτων → Platon

“Beijing”
“Plato”

Diacritics

sçhon → schon
schøn → schön

“already”
“beautiful”

Ligatures

œde → öde
Ærger → Ärger

“bleak”
“trouble”

(pseudo-) Allographs

h@t → huch

“oops”

TAGH Morphology (morph)

Sketch

(Geyken & Hanneforth, 2006)

- Model (conventional) morphological processes as WFST
- Provides *weighted target language* for subsequent methods
 - ▶ analysis cost \approx derivational complexity
- “Known-wins” filtering

$$w \mapsto w : \Leftarrow w \in \pi_1(M_{\text{morph}})$$

Overgeneration: ‘known’ form *shouldn’t always win*

hab \mapsto *hab _{VVIMP}	\neq habe	“have”
Andre \mapsto *André _{NE}	\neq Andere	“other”
muste \mapsto *mus te	\neq muss te	“must”
Grad \mapsto *Grad	\neq Gerade	“directly”
schafsinnig \mapsto *schaf sinnig	\neq scharfsinnig	“perceptive”

- **Workaround:** *safety heuristics*, e.g. *_{V. imp}, *_{NE}, *_f = 0

Phonetic Equivalence (eqpho)

Sketch

$$w \sim_{\text{pho}} v : \Leftrightarrow \text{pho}(w) = \text{pho}(v)$$

- **Idea:** conflate words by *phonetic form* (Jurish, 2008, 2010b)
- **Implementation:** text-to-speech rule-set
 - ▶ modified & compiled as FST M_{pho}
 - ▶ online k -best equivalence cascade search (Jurish, 2010a)

$$C_{\text{eqpho}} := M_{\text{pho}} \circ M_{\text{pho}}^{-1} \circ \pi_1(M_{\text{morph}})$$

Examples

Successes	betrib	↔	Betrieb	“operation”
	eindoitig	↔	eindeutig	“univocal”
	hallooooo	↔	hallo	“hello”
Failures	mirsch	⊟	mich	“me”
	nischt	⊟	nicht	“not”

- **Workarounds:** target language pruning, cascade lookup cutoffs

Rewrite Cascade (rw)

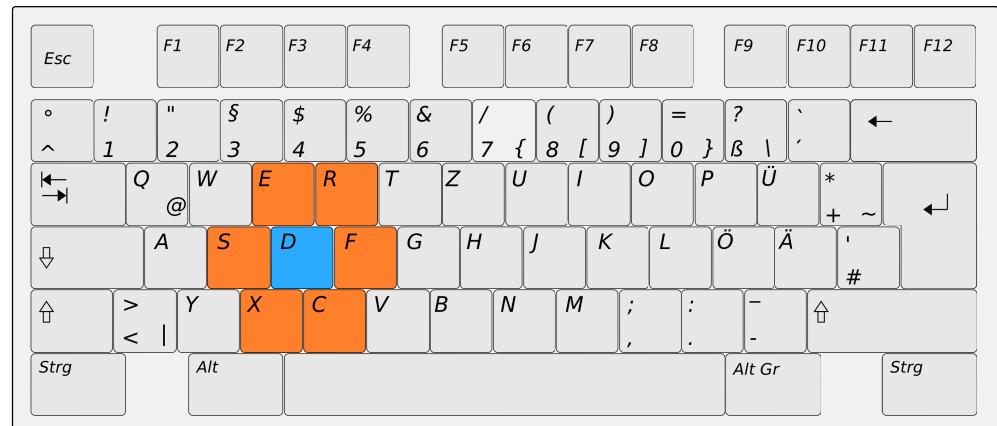
Sketch

$$\begin{aligned}\text{best}_{\text{rw}}(\textcolor{orange}{w}) &:= \arg \min_{\textcolor{blue}{v} \in \mathcal{A}^*} [\![M_{\text{rw}} \circ \pi_1(M_{\text{morph}})]\!](\textcolor{orange}{w}, \textcolor{blue}{v}) \\ \textcolor{orange}{w} \sim_{\text{rw}} \textcolor{blue}{v} &\Leftrightarrow \text{best}_{\text{rw}}(\textcolor{orange}{w}) = \text{best}_{\text{rw}}(\textcolor{blue}{v})\end{aligned}$$

- **Idea:** map words to *nearest* conventional type (Jurish, 2010b,c)
 - ▶ generalized string edit distance (Levenshtein, 1966)
 - ▶ computable even for infinite lexica (Mohri, 2002; Jurish, 2010a)
- **Implementation:** online ($k = 1$)—best cascade search
 - ▶ editor WFST M_{rw} compiled from *keyboard adjacency model*
 - ▶ weight interpolation constants λ_{rw} and λ_{morph}

Keyboard Adjacency

- limit search space
- attenuate edit costs
- insert, delete, replace
- ... but **NOT** transpose!



Error Model M_{rw}

Generic Edit Operations

Deletion	gu <u>e</u> t → gut	“good”
Insertion	is → is <u>t</u>	“is”
Substitution	go <u>ht</u> → <u>ge</u> ht	“goes”
Transposition	udn → u <u>nd</u>	“and”
Doubling	da <u>s</u> → da <u>ss</u>	“that”
Un-doubling	neu <u>ee</u> s → neu <u>e</u> s	“new”
Un-potentiation	juh <u>uuuu</u> → juhu	“woo-hoo”

Keyboard-Adjacent Edit Operations

Deletion	<u>i</u> ommer → im <u>me</u> r	“always”
	ho <u>i</u> → hi	“hi”
Insertion	<u>z</u> → zu	“to”
	scha <u>f</u> → schar <u>f</u>	“sharp”
Substitution	guv <u>k</u> t → gu <u>c</u> kt	“looks”

Token-wise Disambiguation (hmm)

Idea

(Mays et al., 1991; Brill & Moore, 2000; Jurish, 2010c)

- Allow high-recall overgeneration at type level
- Recover precision using token-level context

Implementation: Dynamic Hidden Markov Model (HMM)

- States** are word-conflator pairs

$$\mathcal{Q} = (\mathcal{W} \cup \{\mathbf{u}\}) \times \mathcal{R}$$

- Observations** are input strings

$$\mathcal{O}_S = \bigcup_{i=1}^{n_S} \{\mathbf{w}_i\} \subset \mathcal{A}^*$$

- Transitions (static)**

$$A(\langle \tilde{w}_i, r_i \rangle_{i=1}^m) \approx p(\tilde{w}_m | \tilde{w}_1^{m-1})$$

- Lexicon (dynamic)**: Maxwell-Boltzmann distribution

$$B(\langle \tilde{w}, r \rangle, w) \approx \frac{b^{\beta d_r(w, \tilde{w})}}{\sum_{r' \in \mathcal{R}} \sum_{\tilde{w}' \in \downarrow[w]_{r'}} b^{\beta d_{r'}(w, \tilde{w}')}}$$

- b, β are global model parameters ($b \geq 1, \beta \leq 0$)
- $d_r(w, \tilde{w})$ depends on conflator r
- Lookup (moot)**: Viterbi Algorithm

(Viterbi, 1967)

HMM Example

Input halloo wida muste kuz w€g

HMM Example

Input halooo wida muste kuz w€g

xlit *halooo* *wida* *muste* *kuz* *wEg*

HMM Example

Input halooo wida muste kuz w€g

xlit	<i>halooo</i>	<i>wida</i>	<i>muste</i>	<i>kuz</i>	<i>wEg</i>
pho	{ <i>hallo</i> }	$\left\{ \begin{array}{l} \text{wider,} \\ \text{wieder} \end{array} \right\}$	{ <i>muste</i> }	$\left\{ \begin{array}{l} \text{Cuts,} \\ \text{Kuts} \end{array} \right\}$	$\left\{ \begin{array}{l} \text{weck,} \\ \text{weg} \end{array} \right\}$

HMM Example

Input halloooo wida muste kuz wEg

xlit	<i>halloo</i>	<i>wida</i>	<i>muste</i>	<i>kuz</i>	<i>wEg</i>
pho	{ <i>hallo</i> }	{ <i>wider,</i> <i>wieder</i> }	{ <i>muste</i> }	{ <i>Cuts,</i> <i>Kuts</i> }	{ <i>weck,</i> <i>weg</i> }
rw	<i>hallo</i>	<i>Weda</i>	<i>musste</i>	<i>kurz</i>	<i>weg</i>

HMM Example

Input halloooo wida muste kuz w ϵ g

xlit	<i>halloo</i>	<i>wida</i>	<i>muste</i>	<i>kuz</i>	<i>wEg</i>
pho	{ <u>hallo</u> }	$\left\{ \begin{array}{l} \text{wider,} \\ \text{wieder} \end{array} \right\}$	{ <u>muste</u> }	$\left\{ \begin{array}{l} \text{Cuts,} \\ \text{Kuts} \end{array} \right\}$	$\left\{ \begin{array}{l} \text{weck,} \\ \text{weg} \end{array} \right\}$
rw	<u>hallo</u>	Weda	<u>musste</u>	<u>kurz</u>	<u>weg</u>
hmm	<i>hallo</i>	<i>wieder</i>	<i>musste</i>	<i>kurz</i>	<i>weg</i>

HMM Example

Input hallooo wida muste kuz wEg

xlit	<i>hallooo</i>	<i>wida</i>	<i>muste</i>	<i>kuz</i>	<i>wEg</i>
pho	{ <u>hallo</u> }	$\left\{ \begin{array}{l} \text{wider,} \\ \text{wieder} \end{array} \right\}$	{ <u>muste</u> }	$\left\{ \begin{array}{l} \text{Cuts,} \\ \text{Kuts} \end{array} \right\}$	$\left\{ \begin{array}{l} \text{weck,} \\ \text{weg} \end{array} \right\}$

rw hallo Weda musste kurz weg

hmm hallo wieder musste kurz weg

Output **hallo** **wieder** **musste** **kurz** **weg**

Some Anticipated Difficulties

Lexical

- neologisms & “missing” lexemes
- **Workaround:** static exception lexicon M_{exlex}

ne \mapsto eine “a”
ma \mapsto mal “once”

Morphological*

- “missing” productive processes
- **Workaround:** M_{morph} plug-in(s)

glaub \mapsto glaube “believe”
welch \mapsto welchen “which”

* ... or typographical simulations of phonological processes acting on inflectional morphemes?

Phonetic / Phonological

- identity criterion is too strict
- **Workaround:** M_{rw} plug-in(s)

sehn ~ sehen “see”
zehn $\not\sim$ Zehen “ten”

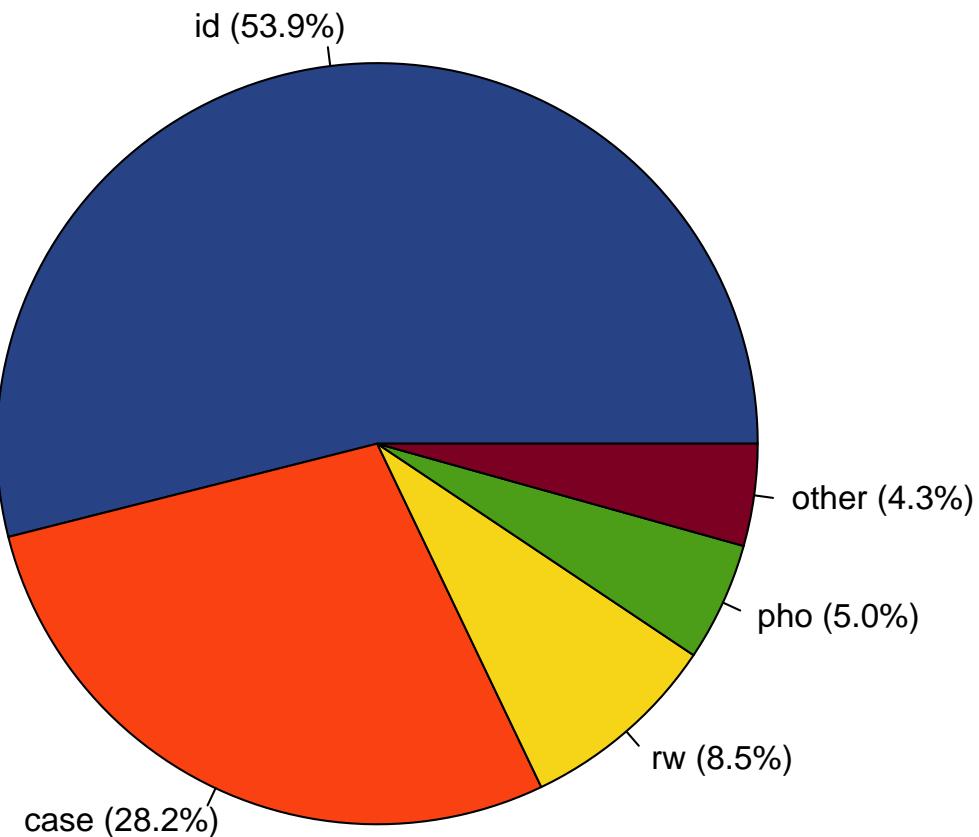
Suprasegmental

- unclear token boundaries
- **Workaround:** ???

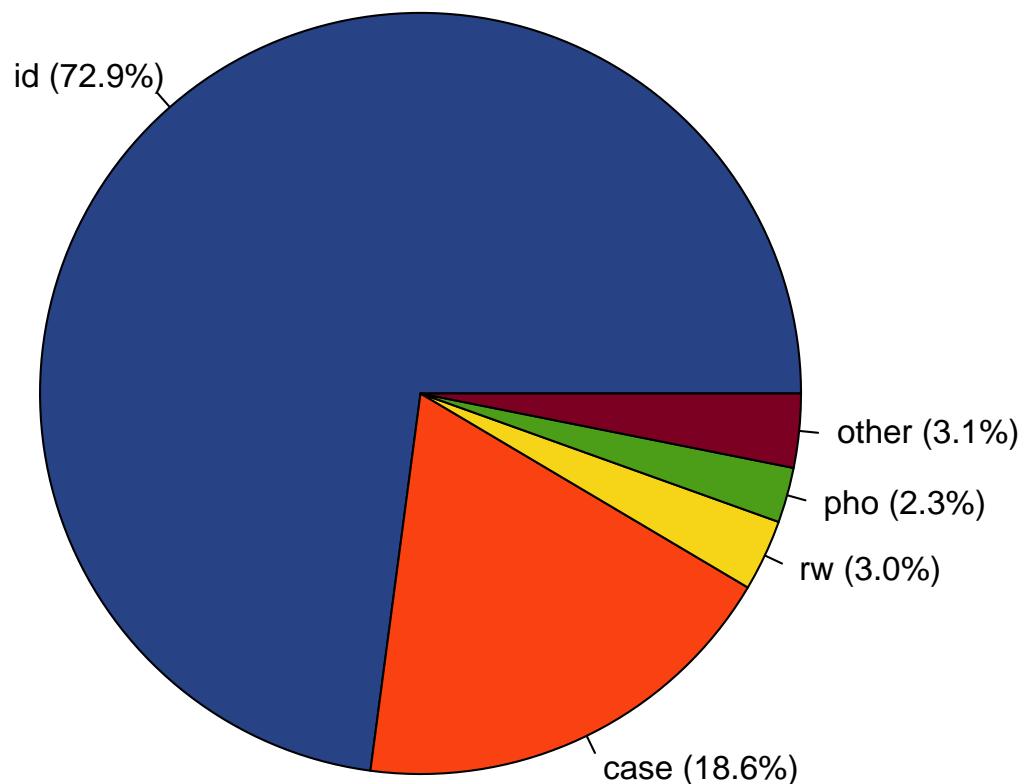
hat's \mapsto hat es “has it”
kannste \mapsto kannst du “can you”

Observed Mappings

by Type ($N = 4340$)



by Token ($N = 13611$)



Concluding Remarks

Unconventional Text and Conventional Tools

won't play together nicely "out of the box"

Canonicalization Methods

Future Work

- part-of-speech annotations *STTS*
 - plug-in resources $M_{\text{exlex}}, M_{\text{rw}}, M'_{\text{morph}}$
 - model parameter optimization ≥ 27 free parameters

C U L8R DØØD\$

(“The End”)

Thank you for listening!