A Multi-purpose Bayesian Model for Word-Based Morphology

Maciej Janicki

University of Leipzig

September 17, 2015



Maciej Janicki A Multi-purpose Bayesian Model for Word-Based Morphology

Introduction

The Model

Experiments

Conclusion

Morphology in NLP

wahrscheinlichster

wahr-schein-lich-st-er

 $wahr(ADJ)-schein(NN)-lich(SUFF_ADJ)-st(SUP)-er(M.SG.NOM)$



Maciej Janicki A Multi-purpose Bayesian Model for Word-Based Morphology

Morphology in NLP

wahrscheinlichster

```
wahr-schein-lich-st-er
```

 $wahr(ADJ)-schein(NN)-lich(SUFF_ADJ)-st(SUP)-er(M.SG.NOM)$

provided:

• morpheme segmentation (with or without tags)

needed:

- is a valid word?
- lemma, possible tags (PoS, inflectional)
- other word features



Conclusion

Whole Word Morphology





Conclusion

Whole Word Morphology





Conclusion

Whole Word Morphology



- concentrates on relations between words
- no "absolute structure/analysis"
- not decomposable
- allows for non-concatenative operations



The Model

. . .

Experiments

Conclusion

Unigram distribution

Let u(w) be the unigram-based probability of the word w.

$$Pr(L) = Pr(|L|) \cdot |L|! \cdot \prod_{w \in L} u(w)$$

. . .

(each word drawn independently from the unigram distribution)



Introduction	The Model	Experiments	Conclusion
Introducing r	ules		

Let a morphological rule $r : /Xe / \rightarrow /Xen /$ be known. r applies from left to right with probability $\pi_r = 0.53$ (productivity).

sprache $2.17 \cdot 10^{-11}$ \rightarrow sprachen 0.53 (*sprachen* derived by *r*)

. . .

. . .



Introduction	The Model	Experiments	Conclusion
Introducing r	rules		

Let a morphological rule $r : /Xe / \rightarrow /Xen /$ be known. r applies from left to right with probability $\pi_r = 0.53$ (productivity).

sprache \rightarrow sprachen	$\begin{array}{c} 2.17 \cdot 10^{-11} \\ 0.53 \end{array} $	sprachen derived by r)
 sprache 2 sprachen	$2.17 \cdot 10^{-11} \cdot 0.47$ $1.88 \cdot 10^{-12}$	(<i>sprachen</i> not derived by <i>r</i>)

Introduction	The Model	Experiments	Conclusion
Lexicon as d	irected graph		



Introduction	The Model	Experiments	Conclusion
Learning			

Model components:

- *L* lexicon (graph)
- R set of rules with their productivities

defined: P(L|R), P(R)

find:

$$\hat{R} = \arg \max_{R} P(R|L)$$

$$= \arg \max_{R} \frac{P(L|R)P(R)}{P(L)}$$

$$= \arg \max_{R} P(L|R)P(R)$$



Conclusion

Learning (cont.)

Supervised learning:

- given L, find R
- extract rules from pairs of related words
- ML estimation for rule productivities



Learning (cont.)

Unsupervised learning:

- given V(L), find E(L) and R
- Find all reasonable edges.
 - find pairs of string-similar words
 - extract rules
 - choose 10k most frequent rules
 - create a "full" graph of all possible edges



Learning (cont.)

Unsupervised learning:

- given V(L), find E(L) and R
- Find all reasonable edges.
 - find pairs of string-similar words
 - extract rules
 - choose 10k most frequent rules
 - create a "full" graph of all possible edges
- Alternating ML estimation of E(L) and R ("hard EM").
 - "guess" an initial R
 - repeat until convergence:
 - find best E(L) given V(L) and R (optimal branching)
 - find best R given V(L) and E(L) (ML estimation)



Lexicon expansion: task definition

- unsupervised training on 50k-wordlists (German, Polish)
- generate new words in the order of increasing cost



Conclusion

Lexicon expansion: results



Lemmatization and Tagging: task definition

- given a word, determine its lemma and PoS/inflectional tag
- training data:
 - supervised: word-lemma pairs
 - unsupervised: a set of words and a set of lemmas (without alignment)
- variants:
 - +/- Lem: lemmas of all unknown words included in the training data?
 - +/- Tags: tag of the target word given?
- baselines:
 - unsupervised: alignment based on least edit distance
 - supervised: Maximum Entropy classifier based on letter N-grams



Lemmatization and Tagging: results

	Data		Results			Baseline		
Language	Lem	Tags	Lem	Tags	Lem+Tags	Lem	Tags	Lem+Tags
	+	+	93%	100%	93%	84%	-	-
Common	+	-	80%	46%	45%	76%	-	-
German	-	+	76%	100%	76%	44%	-	-
	-	-	61%	34%	28%	43%	-	-
	+	+	84%	100%	84%	80%	-	-
Polich	+	-	80%	61%	59%	67%	-	-
FOIISI	-	+	80%	100%	80%	41%	-	-
	-	-	79%	61%	55%	40%	-	-

Data		Results			Baseline			
Language	Lem	Tags	Lem	Tags	Lem+Tags	Lem	Tags	Lem+Tags
	+	+	97%	100%	97%	89%	97%	89%
C	+	-	92%	38%	38%	19%	20%	19%
German	-	+	90%	100%	90%	89%	97%	89%
	-	-	57%	20%	19%	19%	20%	19%
	+	+	94%	100%	94%	83%	94%	83%
Dallah	+	-	93%	56%	56%	33%	36%	33%
Polish	-	+	88%	100%	88%	83%	94%	B 33. C
	-	-	68%	40%	38%	33%	36%	

supervised:

Automatische Sprachverarbeitung

Introduction	The Model	Experiments	Conclusion
Inflection: res	sults		

Task definition:

- given lemma and tag, output the correct inflected form
- baseline: Maximum Entropy classifier based on letter N-grams

Results:

Language	Result	Baseline	
German	84%	83%	
Polish	86%	84%	



Conclusion

- focus on relations between words, rather than segmentation
- non-concatenative morphology included
- many training possibilities: unsupervised, supervised, manual editing
- one model for multiple tasks

