Improving Morphology Induction with Spelling Rules

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Joint Work with Sharon Goldwater

#### Outline

- Morphology Induction
- Our Model
- Hyperparameters & Inference
- Experimental Results
- Conclusion

The study of the internal structure of words:

Antidisestablishmentarianism

The study of the internal structure of words:

Anti.dis.establish.ment.arian.ism

# The study of the internal structure of words:

**Morphemes** 



Anti.dis.establish.ment.arian.ism

# The study of the internal structure of words:



# The study of the internal structure of words:



#### **Unsupervised Morphology Induction**

- Observing just the words, find the best segmentation:
  - $\Box$  walking  $\rightarrow$  walk.ing
- Applications:
  - Important component in many NLP tasks
  - Especially useful for morphologically-rich languages (Finnish, Arabic, Hebrew)
  - Cognitive Science: How do children learn this?

#### Underlying Assumption:

User's Goal: Find best (linguistic) solution.

System Goal: Find most concise solution.

Too Many Stems	<b>Too Many Suffixes</b>	Just Right
walk.	wa.lk	walk.
walks.	wa.lks	walk.s
walking.	wa.lking.	walk.ing
talk.	ta.lk	talk.
talking.	ta.lking	talk.ing
cat.	cat.	cat.
cat.s	cat.s	cat.s
Morphs: 6+2=8	3+5=8	3+3=6

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#### Bayesian Morphology Induction (Goldwater 2006)

P(word) = P(class, stem, suffix) = P(class) x P(stem | class) x P(suffix | class)

Each word consists of a stem and a suffix

 (suffix can be the empty string)

 Multinomials with symmetric Dirichlet priors

 No bias means most concise solution preferable

#### Generative Process: 'walking'



# Generative Process??: 'napping'





#### Spelling Rules



- Rules capture a one-character transformation in a particular context.
- 3 Types: Insertions, Deletions, and Null (no transformation)
- Left context more important in English (we find 2 character left contexts most useful)

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#### A New Generative Process:



#### A New Generative Process:



#### A New Generative Process:



#### Our Model

P(class, stem, suffix, rule type, rule) =

- P(class) x
- P(stem | class) x
- P(suffix | class) x
- P(rule type | context(stem, suffix)) x
- P(rule | rule type, context(stem, suffix))

rule type  $\in$  { Insertion, Deletion, Null }

Greatly increases search space:
About 28 times more possible solutions per word!

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#### Inference

- Alternate between:
  - Gibbs Sampling for the latent variables
    - (class, stems, suffix, etc)
  - Hyperparameter Updates
    - (update hyperparameters over priors on variables)
    - minimize free parameters!
- We run for 5 epochs of:
  - 10 Gibbs Sampling Iterations
  - 10 hyperparameter iterations
- Convergence much earlier

#### Hyperparameters

- Induced for class, stem, suffix, and rule variables
- Learn hyperparameters using Minka's fixed-point method (Minka, 2003)
- Inducing all is principled, but also a computational burden
- Rule type prior set by linguistic intuition:
   hyp(INSERTION) = .001
   hyp(DELETION) = .001
   hyp(NULL) = .5

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#### Data Sets & Evaluation

7487 different verbs from Wall Street Journal
 Gold Standard: CELEX lexical database

 surface segmentation: walk.ing
 abstract representation: 50655+pe

Evaluation Metrics:

Underlying form accuracy

#### **Underlying Form Accuracy**

- Construct the underlying stem from derivational data contained in the CELEX (using lemma ID number)
- Lookup suffix in dictionary:
  - □e3S : -s
  - □a1S : -ed
  - □pe : -ing
- Match strings UFA is % correct

Word	Fo	ound	Gold
state	state+ɛ	<b>٤</b> → <b>٤</b>	44380+i
stating	state+ing	e → ε	44380+pe
states	stat.es	<b>٤</b> → <b>٤</b>	44380+a1S
station	stat+ion	ε → ε	44405+i

Word	Fo	und	Gold
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states	stat.es	$E \rightarrow E$	44380+a1S
station	stat+ion	<b>8</b> → <b>8</b>	44405+i

Word	Found		Gold
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1 match out of 1 arcs = 100% PP for this stem

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1 correct arc out of 2 arcs = %50 Recall for this stem

#### Results: Stems



#### **Results: Suffixes**



#### Induced Rules:

Freq	Rule	Example
468	$e \rightarrow \epsilon$ when before i	abate, abating
41	$\epsilon \rightarrow e$ when after sh/ss/ch	match, matches
29	$\epsilon \rightarrow p$ after p, before i or e	nap, napping

Of the top 20 types of induced rules, 568 of 623 correct = 91 %

Incorrect rules: fated explained as fates.d with s-deletion rates explained as rat.s with an e-insertion

#### Conclusions

- Orthographic rules can help in morphology induction
- Greatly increases search space
- Joint inference over complimentary tasks can overcome the search burden and significantly improve performance in particular parts of task
- This may allow unsupervised generative models to compete more closely with unsupervised discriminative models (with contrastive estimation)

#### Future Work

Extend to multiple suffixes

□ Test on more representative language samples

Test on more languages

- Leverage phonological information for asymmetric priors
  - Once we know 'p' is often doubled, and 't' is similar to 'p', should imply 't' may also often be doubled
  - □May allow for character-to-character transformations
- Hierarchical Models
  - More like grammar induction than segmentation
     Capture interaction between prefixes and suffixes