# Neural Transition-based String Transduction for Limited-Resource Setting in Morphology

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# String Transduction Tasks in Morphology

## String transduction with (optional) features

input string $\mathbf{x}$ + features $\mathbf{f} \rightarrow$ output string $\mathbf{y}$

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or normalization of historical texts, grapheme-to-phoneme, . . .

# General Modeling Objectives of Our Approach

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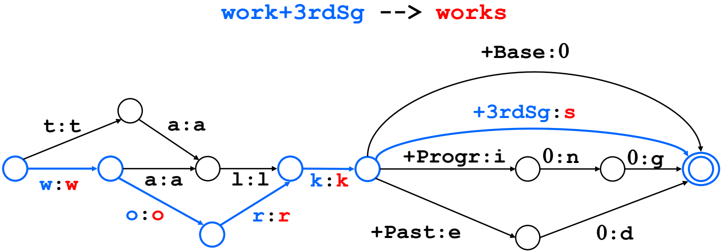
In short, keep it as simple as possible...

# Classical Finite-State Transducers (FST)

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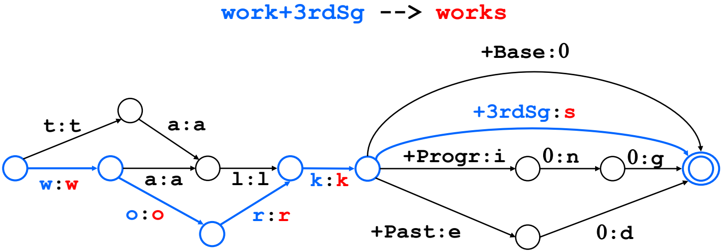


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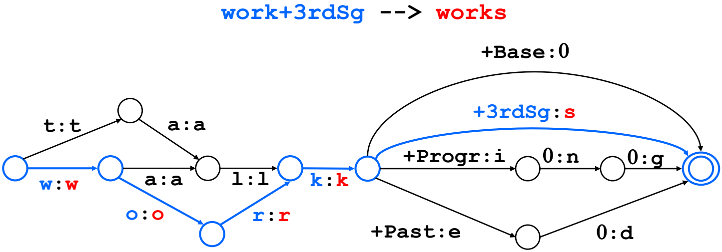


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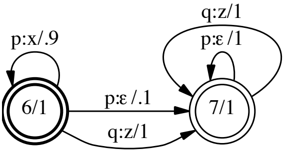
- Fixed transition structure (topology)
- Transitions with 0/1 weights ("Boolean" semiring)
- Rational string relations

# Weighted Finite-State Transducers (WFST) [Mohri, 1997]

- Attach weights to transitions
- Weighted conditional probabilistic relations: $P(\mathbf{y} \mid \mathbf{x}) = \sum_{k \in Paths_{\mathbf{x}:\mathbf{y}}} P(k)$

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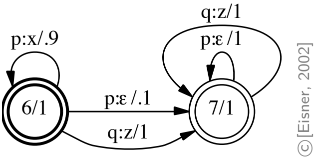


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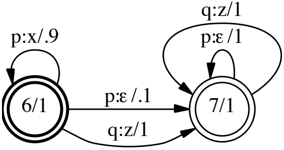


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## Weight Learning Problem [Eisner, 2002]

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## Topology Learning Problem

There are many possibilities for character-level string alignment . . .

```
f l i e g e n    f l i e g e n    f l i e g e n    f l i e g e n
| | | | | | |    | | | | | | |    | | | | | | |    | | | | | | |
f l   o g        f l o   g        f l o g          f l       o g
```

# LAT: "Latent-Variable Modeling of String Transductions with Finite-State Methods" [Dreyer et al., 2008]

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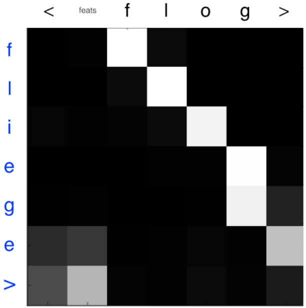
- Suffers on small datasets
- Attention is crucial for performance

# Soft Attention in Morphological Reinflection

## Where does soft attention concentrate?

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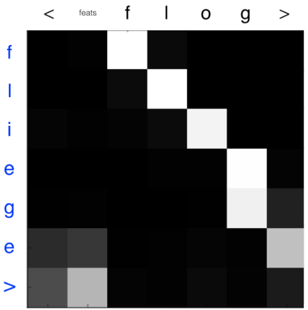


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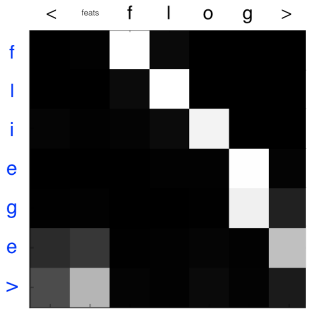


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## Character alignment strategies

CRP Mans Hulden's stochastic Chinese Restaurant Process aligner

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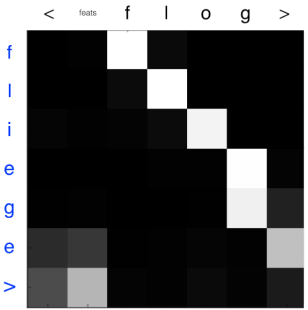


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LCS Simple deterministic Longest Common Substring + pre-/suffixation

```
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# HA: "Morphological Inflection Generation with Hard Monotonic Attention" [Aharoni and Goldberg, 2017]

## Inflection example

```
f l o   g
| | | | | | |
f l i e g e n
```

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | $t$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ⟨s⟩ | | f | | l | | o | | | g | | | | ⟨/s⟩ | $y$ |
| ⟨s⟩ | STEP | f | STEP | l | STEP | o | STEP | STEP | g | STEP | STEP | STEP | ⟨/s⟩ | $a_t$ |
| ⟨s⟩ | ⟨s⟩ | f | f | l | l | i | i | e | g | g | e | n | ⟨/s⟩ | $x_i$ |
| 0 | 0 | 1 | 1 | 2 | 2 | 3 | 3 | 4 | 5 | 5 | 6 | 7 | 8 | $i$ |

## Key ideas of transduction machine

- Given input **x** and **f**, predict action sequence **a** of a transition machine with read and write tapes!

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- Gold oracle action sequence **a** for training set is determined by an external monotonic character aligner (CRP)

# HA: Encoding, Decoding and Hard Attention

**BiLSTM encoding of input $\mathbf{x} = x_1 \dots x_n$** $E(\cdot)$=embedding

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$$P(a_t = k \mid \mathbf{a}_{<t}, \mathbf{x}, \mathbf{f}, \Theta) = \mathrm{softmax}_k(\mathbf{W} \cdot \mathbf{s}_t + \mathbf{b})$$

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**Hard attention of decoder**

"Neuralese" for looking only at a single (BiLSTM encoded) character $\mathbf{h}_i$

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## Key additions of our approach to HA

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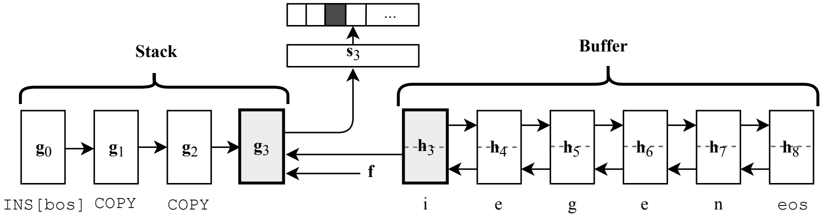
## Edit actions as state transition operations

- DELETE: pop next character from input buffer
- COPY: pop next character from input buffer and append it to output
- INSERT $c$: append character $c$ to output

# Example Transduction “fliegen” → “flog”




| $t$ | Transition $a_t$ | Output y | Stack | Buffer |
|---|---|---|---|---|
| 0 | INSERT(BOS) | [] | [INSERT(BOS)] | [f,l,i,e,g,e,n,EOS] |

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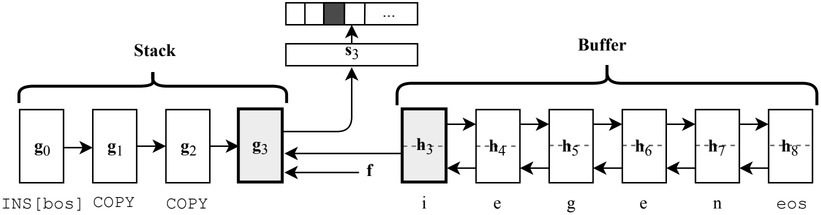


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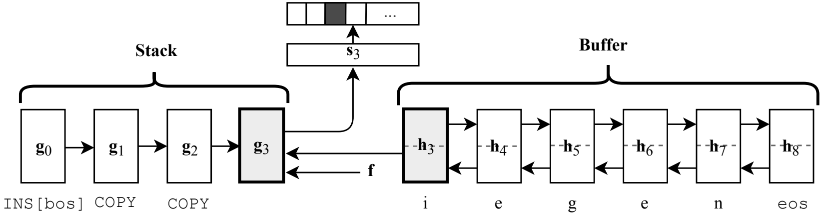


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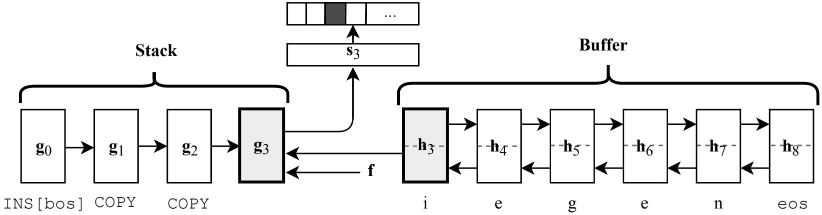


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| 3 | DELETE | [f, l] | [DELETE,COPY, . . . ] | [e,g,e,n,EOS] |
| 4 | DELETE | [f, l] | [DELETE, DELETE, . . . ] | [g,e,n,EOS] |
| 5 | INSERT($o$) | [f, l, o] | [INSERT($o$), DELETE, . . . ] | [g,e,n,EOS] |
| 6 | COPY | [f, l, o, g] | [COPY, INSERT($o$), . . . ] | [e,n,EOS] |
| 7 | DELETE | [f, l, o, g] | [DELETE, COPY, . . . ] | [n,EOS] |
| 8 | DELETE | [f, l, o, g] | [DELETE, DELETE, . . . ] | [EOS] |
| 9 | INSERT(EOS) | [f, l, o, g] | | |

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- and the full input context through BiLSTM input encoding
- Beam search alleviates issues from greedy decoding

# MLE Training of State-Transition System

Training data $D$ are pairs of input strings **x** and *transition sequences* **a**

(ignoring features for simplicity)

| Alignment | Input and alignment-derived actions |
|---|---|
| fliegen | (f, l, i, e, g, e, n) |
| fl og | (COPY, COPY, DEL, DEL, INS(o), COPY, DEL, DEL) |

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**Alignment**

```
fliegen
fl  og
```

**Input and alignment-derived actions**

```
(f,    l,    i,    e,            g,    e,    n)
(COPY, COPY, DEL,  DEL,  INS(o), COPY, DEL,  DEL)
```

**Maximize conditional log-likelihood of training data $D$**

$$\mathcal{L}(D, \Theta) = \sum_{(\mathbf{x},\mathbf{a}) \in D} \log P(\mathbf{a} \mid \mathbf{x}; \Theta) = \sum_{(\mathbf{x},\mathbf{a}) \in D} \sum_{i=1}^{|a|} \log P(a_i \mid \mathbf{a}_{<i}, \mathbf{x}; \Theta)$$

Our parameter $\Theta$ maximizes the probability of per-character edits!

# Training Problems

## Loss-evaluation mismatch

We need character sequence accuracy, not edit action probability!

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During training, system sees only gold action history to condition on.

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## Better Training

How can we train the entire system end-to-end?

# One Possible Approach: Minimum Risk Training (MRT)

**Minimize expected risk of training data $T$ consisting of (x,y) pairs**

$$\mathcal{R}(T, \Theta) = \sum_{(\mathbf{x},\mathbf{y}) \in T} \mathbb{E}_{\mathbf{a}|\mathbf{x};\Theta} \left[ \delta(\hat{y}, y) \right]$$

where the risk is a combination ($[-1, 1]$)
of normalized Levenshtein distance $\mathrm{NLD} \in [0, 1]$ and accuracy $\in \{0, 1\}$:

$$\delta(\hat{y}, y) = \mathrm{NLD}(\widehat{\mathrm{y}}, \mathrm{y}) - \mathbb{1}\{\widehat{\mathrm{y}} = \mathrm{y}\}$$

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## Approximation of expectation under posterior $\mathbb{E}_{\mathbf{a}|\mathbf{x};\Theta}[\delta(\hat{y}, y)]$

Sampling from $P(\mathbf{a} \mid \mathbf{x}; \Theta)$ and re-normalizing allows normal gradient training [Shen et al., 2016]

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- Cold start training with MRT is not practical!
- Two stage training regime necessary: First MLE, second MRT!

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- Cold start training with MRT is not practical!
- Two stage training regime necessary: First MLE, second MRT!
- MRT training oscillates and cannot always improve over MLE for all datasets

# Experiments

- For all (!) dataset sizes, our approach uses character and action embeddings of size 100, single-layer LSTMs with hidden size 200
- We apply parameter tying for characters and their insert action as [Aharoni and Goldberg, 2017]
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- MRT training times: a bit longer than MLE if converging, otherwise as long as early stopping patience allows...

# Results on SIGMORPHON 2017 inflection task

| **Model** (averages) | | low | medium | **Model** (ensembles) | | low | medium |
|---|---|---|---|---|---|---|---|
| baseline | | 37.9 | 64.7 | | | 37.9 | 64.7 |
| HA* | LCS | 29.1 | 78.5 | HA*-E | LCS | 31.5 | 80.2 |
| CA | LCS | 47.3 | 79.5 | CA-E | LCS | 48.8 | 81.0 |
| HA* | CRP | 23.9 | 75.4 | HA*-E | CRP | 26.1 | 77.8 |
| CA | CRP | 42.5 | 78.9 | CA-E | CRP | 44.0 | 80.6 |
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| | | | | HAEM-E7 | | 48.5 | 80.3 |
| | | | | HA[EC]M-E15 | | **50.6** | 82.8 |

- 52 languages; low setting (100 training examples); medium (1000)
- Alignment strategies: Stochastic CRP and longest common substring (LCS)
- Averages and ensembles (-E) over 5 models reported

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- CA with COPY mechanism heavily outperforms HA* on low setting
- CA is consistently better than HA* on medium

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- MRT training improves results on low and medium

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- Every system, setting and training profits from ensembling by 1-3 points
- Only our large complex winning ensemble HA[EC]M-E15 from SIGMORPHON is still a bit stronger on low

# Results on CELEX reinflection dataset

| Model | 13SIA | 2PIE | 2PKE | rP | Avg. |
|---|---|---|---|---|---|
| CELEX-BY-TASK | | | | | |
| LAT | **87.5** | 93.4 | 87.4 | 84.9 | 88.3 |
| NWFST | 85.1 | 94.4 | 85.5 | 83.0 | 87.0 |
| HA* | 84.6 | 93.9 | **88.1** | 85.1 | 87.9 |
| CA | 85.0 | 94.5 | 88.0 | 84.9 | 88.1 |
| HA*-MRT | 84.8 | 94.0 | 88.1 | 85.2 | 88.0 |
| CA-MRT | 85.6 | **94.6** | 88.0 | **85.3** | **88.4** |
| CELEX-ALL (ensembles) | | | | | |
| MED | 83.9 | 95.0 | 87.6 | 84.0 | 87.2 |
| HA | 85.8 | **95.1** | **89.5** | 87.2 | 89.5 |
| HA*-E | 85.3 | 94.8 | 88.9 | 87.4 | 89.1 |
| CA-E | 85.8 | 94.9 | 88.8 | 86.7 | 89.1 |
| HA*-MRT-E | 85.8 | 95.0 | 89.2 | **87.7** | 89.4 |
| CA-MRT-E | **86.7** | 94.9 | 89.3 | 87.1 | **89.5** |

CA-MRT on average stronger than all other strong competitors in this medium-sized task

# Results on Lemmatization Dataset [Wicentowski, 2002]

| Model | | basque | english | irish | tagalog | Avg. |
|---|---|---|---|---|---|---|
| Size | | 4.7K | 3.9K | 1.1K | 7.6K | 4.3K |
| LAT | | 93.6 | 96.9 | **97.9** | 88.6 | 94.2 |
| NWFST | | 91.5 | 94.5 | **97.9** | 97.4 | 95.3 |
| HA* | lcs | **97.0** | 97.5 | **97.9** | **98.3** | **97.7** |
| CA | lcs | 96.3 | 96.9 | 97.7 | **98.3** | 97.3 |
| HA* | crp | 96.2 | **97.7** | 97.3 | 97.9 | 97.3 |
| CA | crp | 96.1 | 96.7 | 96.8 | 97.6 | 96.8 |

HA* and CA outperform other approaches by quite some margin in this medium/high resource setting

# Connecting System Performance with Linguistic Properties

## An issue and a proposal

- Datasets sets generally lack explizit per item characterization of covered morphological phenomena, lexical properties (e.g. strong vs weak verbs)
- Automatic assessment of advantages/disadvantages of approaches wrt linguistic properties is difficult

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- Challenge test sets got popular in Neural Machine Translation [Sennrich, 2017, Avramidis et al., 2018].
- Computational morphology could profit from analog initiatives
- We added and released explicit information to all CELEX rP task datasets as an appetizer[a]:
  regular/irregular verbs, "ge" affixation specification

[a] https://gitlab.cl.uzh.ch/morphology-datasets/sigmorphon-2017-format/celex-by-task

# Summary

- Our neural state-transition system that predicts character-wise edit actions performs extremely strong in limited-resource settings and competitive in high settings for typical morphological tasks

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- Our neural state-transition system that predicts character-wise edit actions performs extremely strong in limited-resource settings and competitive in high settings for typical morphological tasks
- We show that in limited-resource settings, MRT training consistently improves results
- General and robust: no language-specific modeling, no feature engineering, almost no hyperparameter tuning

# The End

Thank you for your attention.

Comments? Questions?

Source code

`https://github.com/ZurichNLP/coling2018-neural-trans-based-morphology`

All test set outputs of our system (re)-implementations:

`https://github.com/ZurichNLP/ZurichNLP/`

`coling2018-neural-transition-based-morphology-test-data`


## Acknowledgments

Tatyana Ruzsics, Tanja Samardžić, Mathias Müller, Roee Aharoni, Pushpendre Rastogi, Katharina Kann, and the anonymous reviewers.

# Outlook: Imitation Learning

## Another solution for end-to-end learning

- Dynamic oracle for gold actions
- Imitation learning approach (forthcoming EMNLP 2018 paper)
- No coldstart/warmstart training!
- Best results on all 3 settings in CoNLL-SIGMORPHON 2018 inflection task!

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