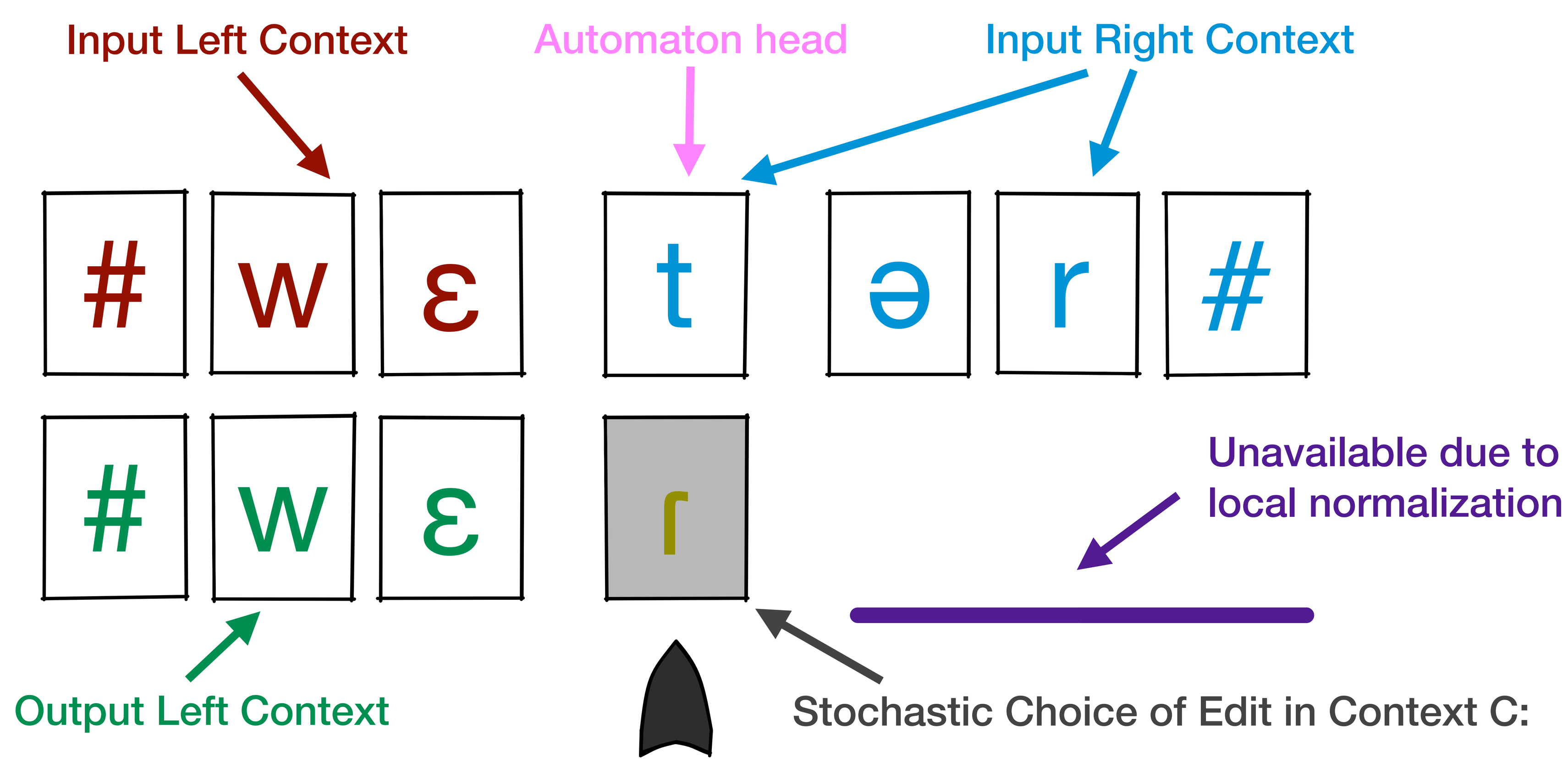
Stochastic Contextual Edit Distance and Probabilistic FSTs

JOHNS HOPKINS UNIVERSITY

Ryan Cotterell, Nanyun Peng, Jason Eisner

Example from English Phonology

Consider the productive case of intervocalic alveolar flapping in American English e.g., compare the pronunciation of *wet* and *wetter*. We should map the underlying form /**wɛtər**/ to its surface form **[wɛɾər]**. This is predicted by a left-to-right, context sensitive editing process:



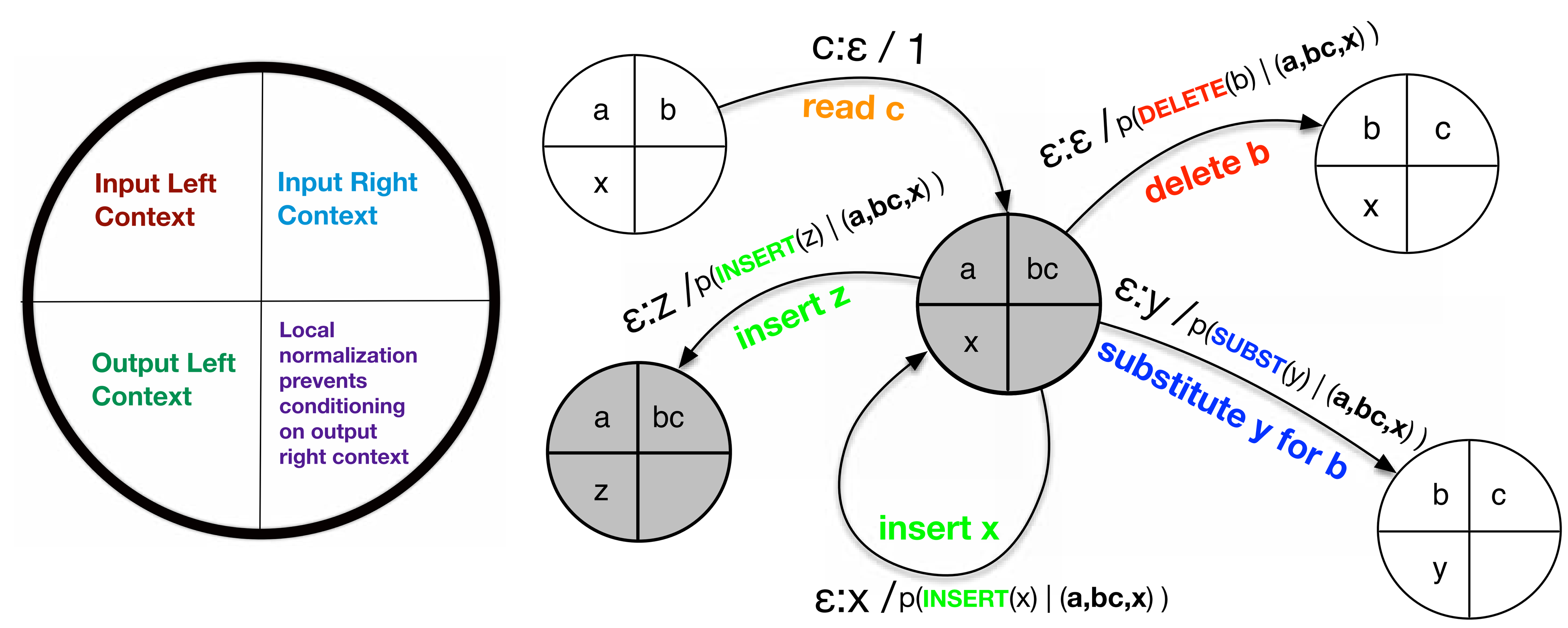
The distribution over possible edits takes the form of a conditional log-linear model:

$$p(e \mid C) \stackrel{\text{def}}{=} \frac{1}{Z_c} \exp\left(\theta \cdot \vec{f}(C, e)\right)$$

$p(\textbf{COPY}[\text{t}] \mid C) = \ldots$
$p(\textbf{INS}[\text{z}] \mid C) = \ldots$
$p(\textbf{SUB}[\text{t}, \text{ɾ}] \mid C) = \ldots$
$p(\textbf{DEL}[\text{t}] \mid C) = \ldots$
...

The Contextual Edit Transducer

- We define a conditional probability distribution of an *edit* given a *context* using a log-linear model.
- An edit is one of four actions: COPY, SUBSTITUTE, DELETE or INSERT.
- The probability of a sequence of edits is a product where each edit's probability is conditioned on the context produced by the previous edits.
  - A context consists of three context windows: input left, input right and output left.
  - Right output context is unavailable in PFSTs, so the model is left/right asymmetric.
- For $x, y \in \Sigma^*$, let $p(y \mid x)$ be the total probability of all edit sequences that map x into y. Note that $\sum_y p(y \mid x) = 1, \forall x$.
- We construct a single probabilistic finite-state transducer to compute $p(y \mid x)$.



Training

Given (x_k, y_k) with unobserved alignments (edit sequences), EM will locally maximize $\sum_k p(y_k \mid x_k)$. The E-step sums over all x_k-to-y_k alignment paths in the transducer (forward-backward algorithm). The M-step uses L-BFGS. The gradient takes the following well-known form:

$$\sum_{C,e} c(C,e)\left[\vec{f}(C,e) - \sum_{e'} p_\theta(e' \mid C)\vec{f}(C,e')\right].$$

When L-BFGS is not run to convergence we recover a generalized EM algorithm, which is more efficient because we do not keep adjusting parameters based on out-of-date counts.

Algorithm 1 Training a PFST T_θ by EM.

- **while** not converged **do**
  - reset all counts to 0 ▷ begin the "E step"
  - **for** $k \leftarrow 1$ **to** K **do** ▷ loop over training data
    - $M = x_k \circ T_\theta \circ y_k$ ▷ small acyclic WFST
    - $\vec{\alpha}$ = FORWARD-ALGORITHM(M)
    - $\vec{\beta}$ = BACKWARD-ALGORITHM(M)
    - **for** arc $A \in M$, from state $q \to q'$ **do**
      - **if** A was derived from an arc in T_θ representing edit e, from edit state q_C, **then**
        - $c(C, e) \mathrel{+}= \alpha_q \cdot \text{prob}(A) \cdot \beta_{q'} / \beta_{q_I}$
  - $\theta \leftarrow$ L-BFGS(θ, EVAL, max_iters=5) ▷ the "M step"
- **function** EVAL(θ) ▷ objective function & its gradient
  - $F \leftarrow 0; \nabla F \leftarrow 0$
  - **for** context C such that $(\exists e) c(C, e) > 0$ **do**
    - *count* $\leftarrow 0$; *expected* $\leftarrow 0$; $Z_C \leftarrow 0$
    - **for** possible edits e in context C **do**
      - $F \mathrel{+}= c(C, e) \cdot (\theta \cdot \vec{f}(C, e))$
      - $\nabla F \mathrel{+}= c(C, e) \cdot \vec{f}(C, e)$
      - *count* $\mathrel{+}= c(C, e)$
      - *expected* $\mathrel{+}= \exp(\theta \cdot \vec{f}(C, e)) \cdot \vec{f}(C, e)$
      - $Z_C \mathrel{+}= \exp(\theta \cdot \vec{f}(C, e))$
    - $F \mathrel{-}= \textit{count} \cdot \log Z_C$; $\nabla F \mathrel{-}= \textit{count} \cdot \textit{expected} / Z_C$
  - **return** $(F, \nabla F)$

Probabilistic vs. Weighted Finite-State Transducers

PFSTs are locally normalized models. WFSTs, which are globally normalized models, do not suffer from *label bias* and are likely to beat PFSTs as a linguistic model. The distinction is identical to that between a MEMM and a CRF. So why are we interested in PFSTs?

Comparative Advantages

PFSTs

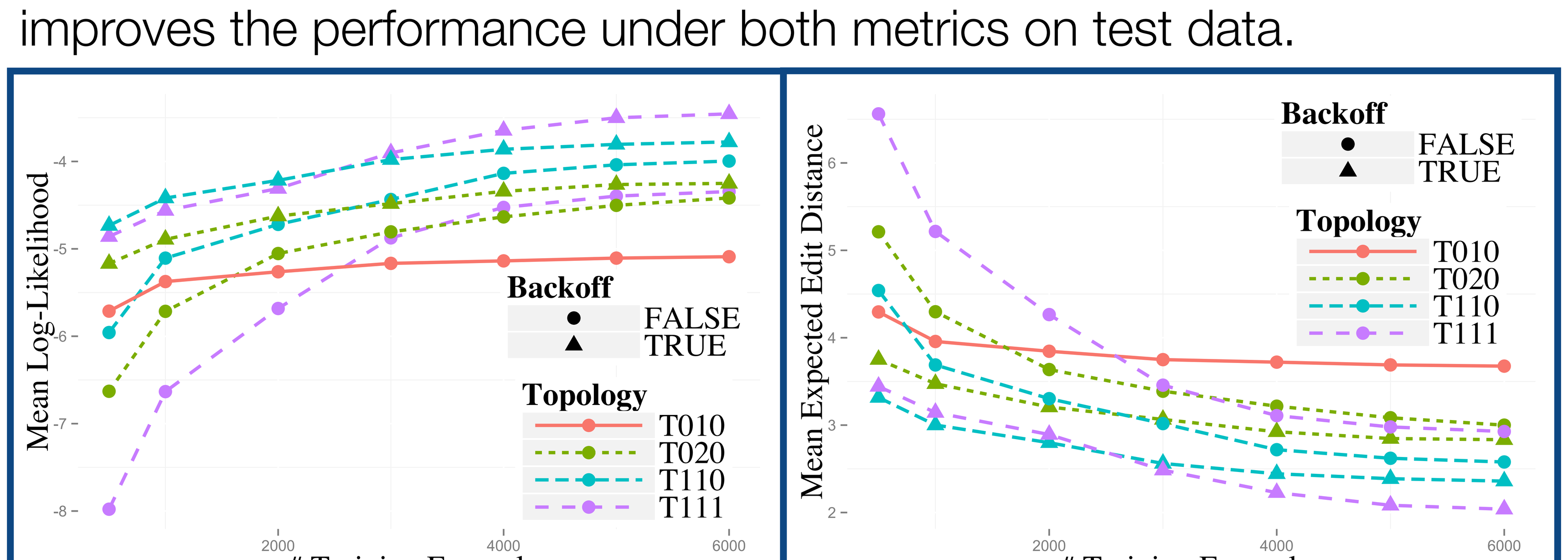
- PFSTs do not require the computation of a separate partition function Z_x for every x. This makes them tractable when x is uncertain e.g., in noisy channel models, channel cascades and Bayesian networks.
- PFSTs are more efficient to train under conditional likelihood. It is faster to compute the gradient, since we only have to raise the probabilities of arcs in $x_k \circ T \circ y_k$ relative to competing arcs in $x_k \circ T$.

WFSTs

- A WFST's advantage is that the probability of an edit can be indirectly affected by the weights of other edits at a distance.
- One could construct WFSTs where an edit's weight directly considers local right output context.
- WFSTs can also use a simpler topology while retaining determinism, since edits can be scored "in retrospect" after they have passed into the left context.

Experiments

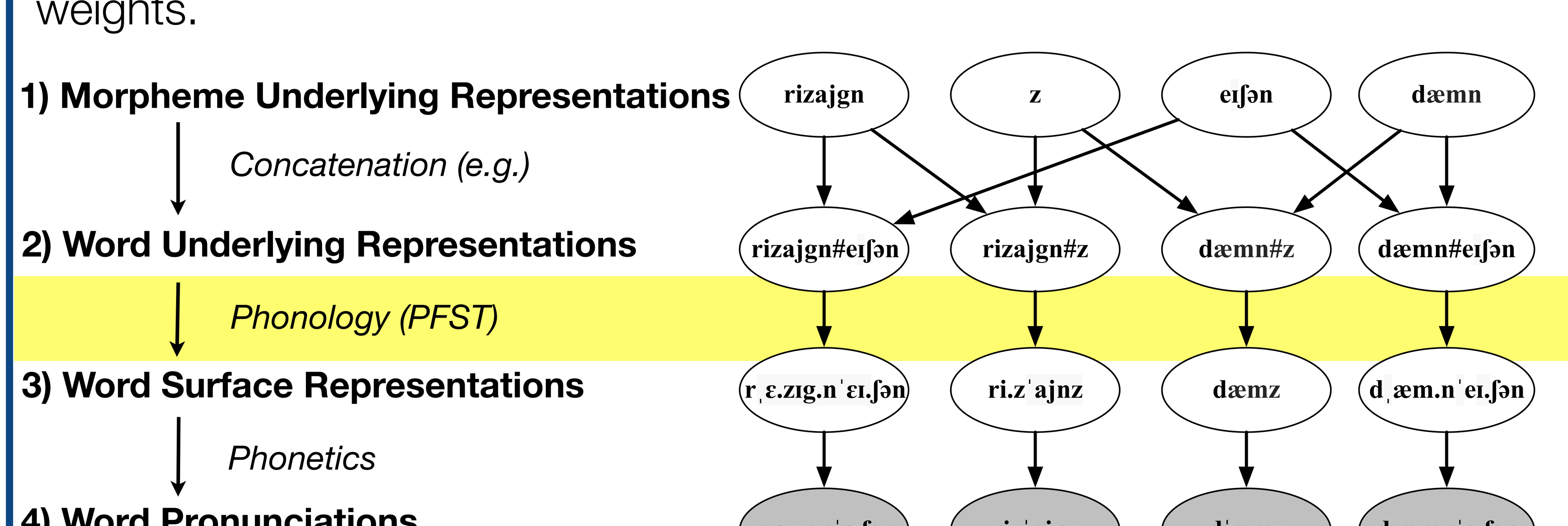
To demonstrate the utility of *contextual* edit transducers, we examine spelling errors in social media data. We report on test data how much probability mass lands on the true y_k. We also report how much mass lands "near" y_k, by measuring the expected edit distance of the predicted y to the truth. The graphs show that more context improves the performance under both metrics on test data.



We use four different **topologies** (context configurations). Note that (0,1,0) is standard weighted edit distance. We also use **backoff** features that each context shares with other contexts and L_2 regularization.

Future Work - Inferring Underlying Forms

We will use a PFST with features inspired by linguistic theory to model phonology within a Bayesian network. Observed pronunciations are often explained as arising from the "underlying forms" of morphemes. Linguists try to reconstruct these latent strings. Our technique involves loopy belief propagation in a generative (directed) graphical model whose variables are unknown strings and whose factors are finite-state machines with unknown weights.



See Keynote at **MORPHFSM** on **Friday** at **9:15am** for more details.