CS11-747 Neural Networks for NLP

Unsupervised and Semi-supervised Learning of Structure

Graham Neubig

Carnegie Mellon University
Language Technologies Institute

Site
https://phontron.com/class/nn4nlp2020/

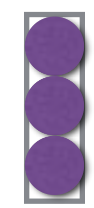
Supervised, Unsupervised, Semi-supervised

- Most models handled here are **supervised** learning
  - Model P(Y|X), at training time given both
- Sometimes we are interested in **unsupervised** learning
  - Model P(Y|X), at training time given only X
- Or **semi-supervised** learning
  - Model P(Y|X), at training time given both or only X

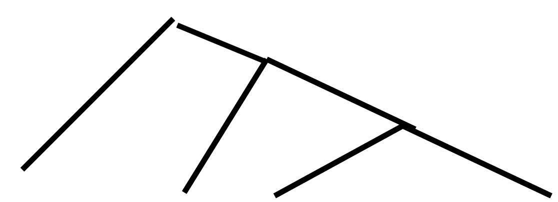
Learning Features vs. Learning Structure

Learning Features vs. Learning Discrete Structure

- Learning features, e.g. word/sentence embeddings:

this is an example $\longrightarrow$ 

- Learning discrete structure:



this is an example $\longrightarrow$ this is an example

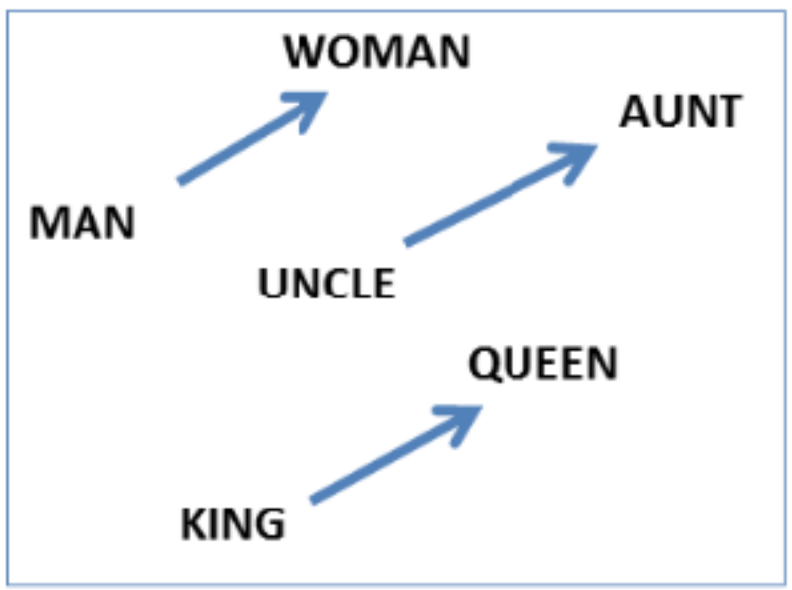
- Why discrete structure?
  - We may want to model information flow differently
  - More interpretable than features?

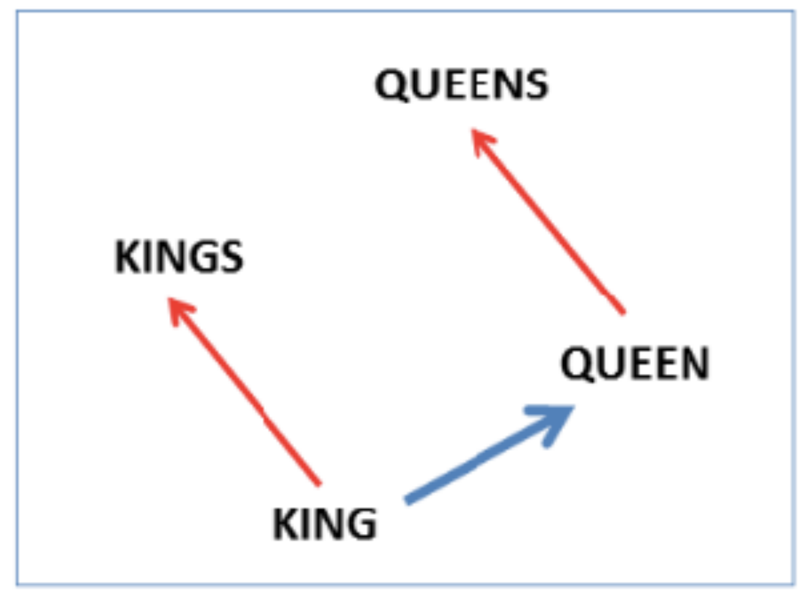
Unsupervised Feature Learning (Review)

- When learning embeddings, we have an objective and use the intermediate states of this objective
    - CBOW
    - Skip-gram
    - Sentence-level auto-encoder
    - Skip-thought vectors
    - Variational auto-encoder

How do we Use Learned Features?

- To solve tasks directly (Mikolov et al. 2013)





  - And by proxy, knowledge base completion, etc., to be covered in a few classes

- To initialize downstream models

What About Discrete Structure?

- We can cluster words
- We can cluster words in context (POS/NER)
- We can learn structure

What is our Objective?

- Basically, a generative model of the data X
- Sometimes factorized $P(X|Y)P(Y)$, a traditional generative model
- Sometimes factorized $P(X|Y)P(Y|X)$, an auto-encoder
    - This can be made mathematically correct through variational autoencoder $P(X|Y)Q(Y|X)$

Clustering Words in Context

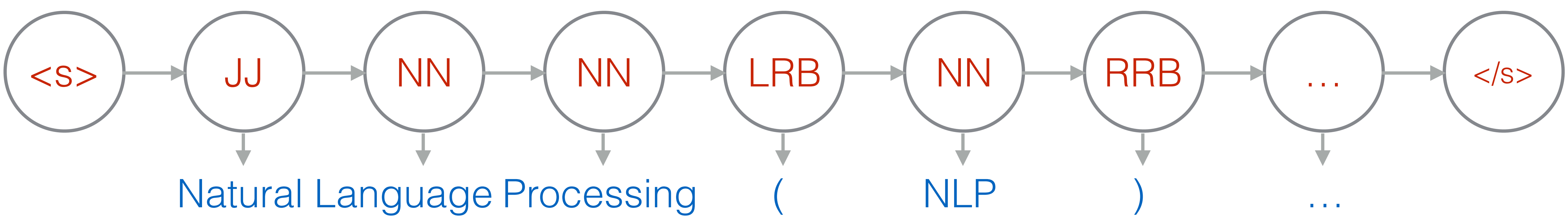
A Simple First Attempt

- Train word embeddings
- Perform k-means clustering on them
- Implemented in word2vec (-classes option)
- But what if we want single words to appear in different classes (same surface form, different values)

Hidden Markov Models

- Factored model of P(X|Y)P(Y)
- State→state **transition** probabilities
- State→word **emission** probabilities

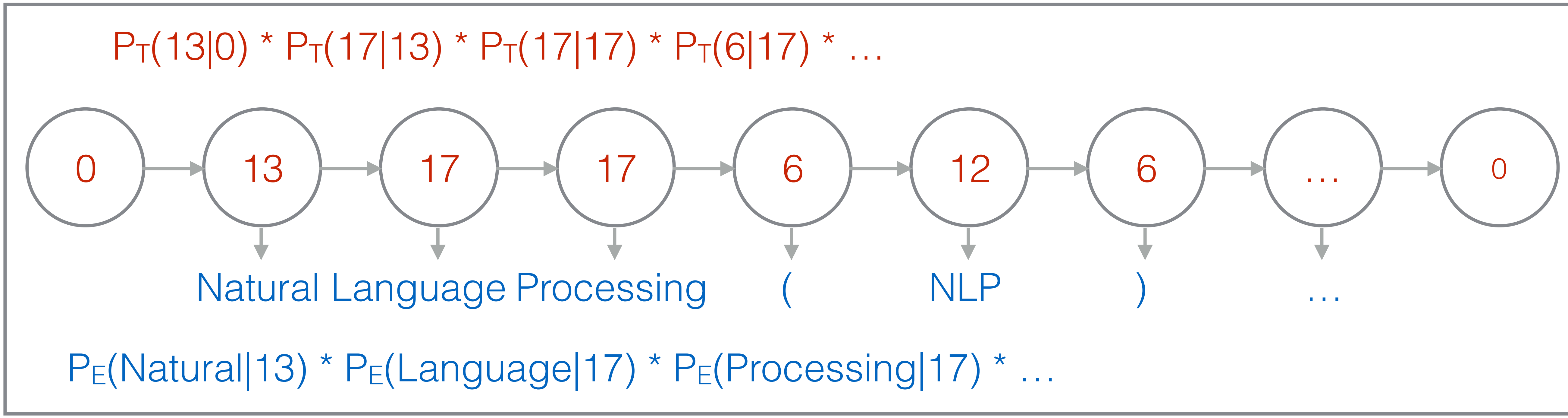
$P_T(JJ|<s>) * P_T(NN|JJ) * P_T(NN|NN) * P_T(NN|LRB) * \ldots$



$P_E(Natural|JJ) * P_E(Language|JJ) * P_E(Processing|JJ) * \ldots$

Unsupervised Hidden Markov Models

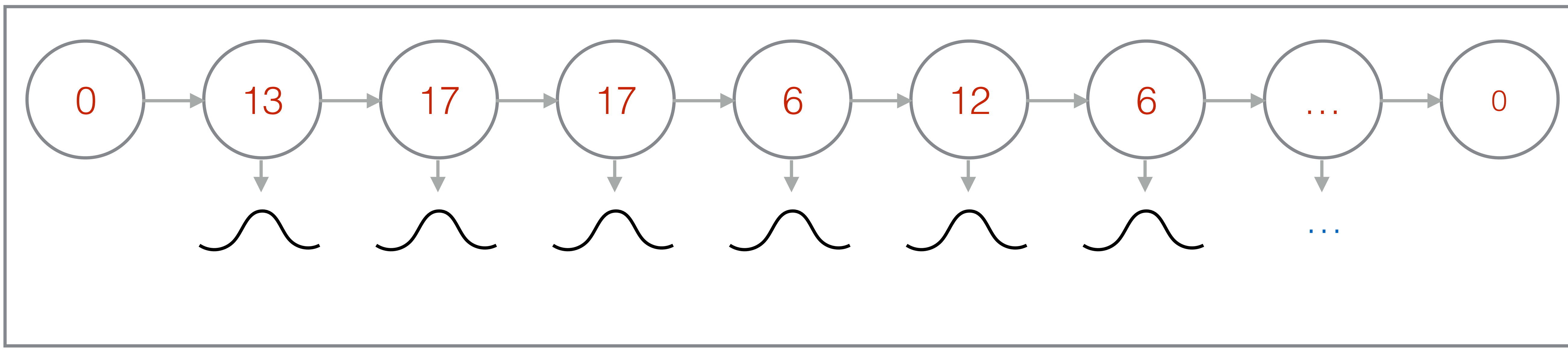
- Change label states to unlabeled numbers



- Can be trained with forward-backward algorithm

Hidden Markov Models w/ Gaussian Emissions

- Instead of parameterizing each state with a categorical distribution, we can use a Gaussian (or Gaussian mixture)!



- Long the defacto-standard for speech
- Applied to POS tagging by training to emit word embeddings by Lin et al. (2015)

A Simple Approximation: State Clustering (Giles et al. 1992)

- Simply train an RNN according to a standard loss function (e.g. language model)
- Then cluster the hidden states according to k-means, etc.

Featurized Hidden Markov Models (Tran et al. 2016)

- Calculate the transition/emission probabilities with neural networks!
  - **Emission:** Calculate representation of each word in vocabulary w/ CNN, dot product with tag representation and softmax to calculate emission prob
  - **Transition Matrix:** Calculate w/ LSTMs (breaks Markov assumption)

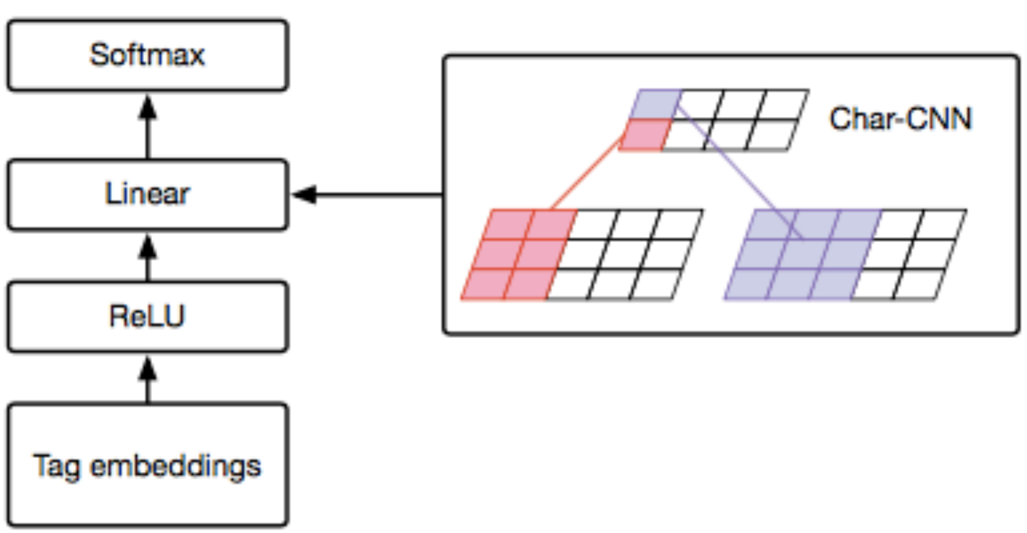


Figure 2: Computational graph of Char-CNN emission network. A character convolutional neural network is used to compute the weight of the linear layer for every minibatch.

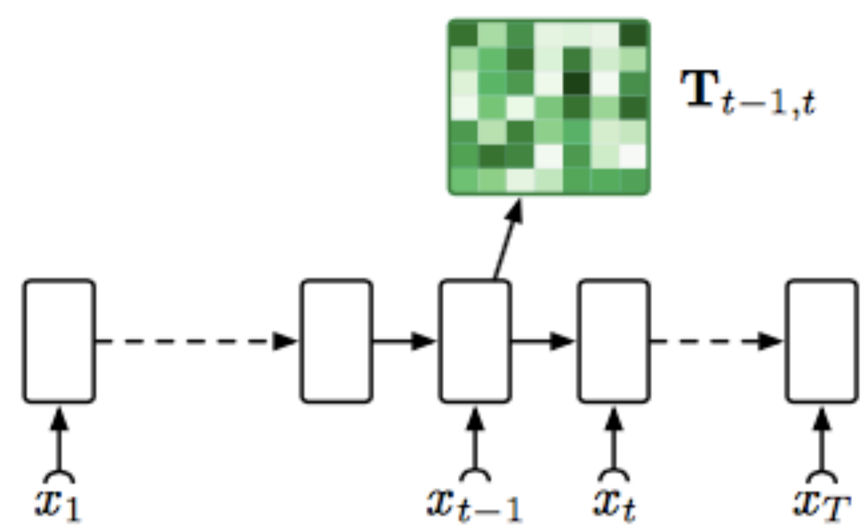
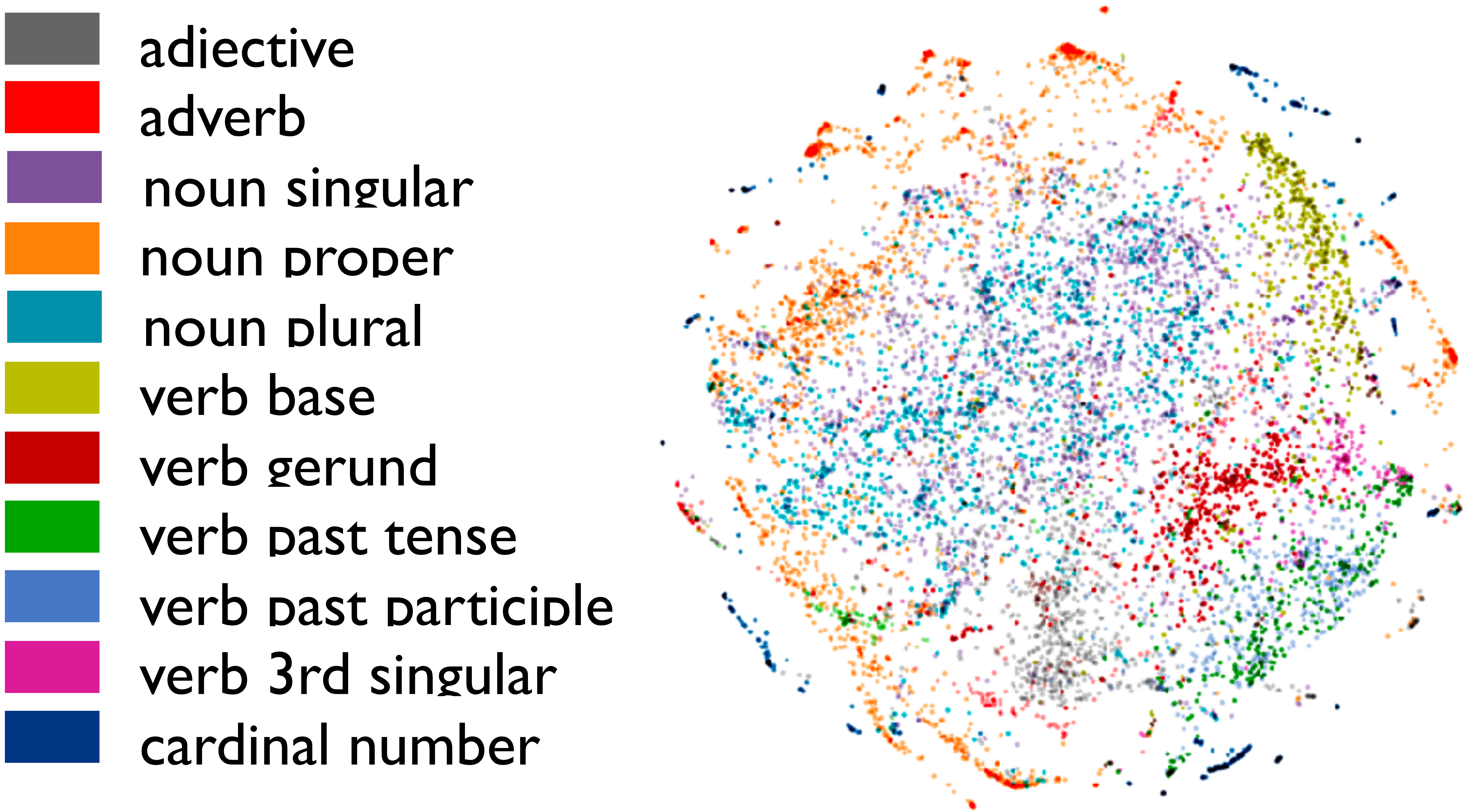


Figure 3: A graphical representation of our LSTM transition network. Transition matrix $\mathbf{T}_{t-1,t}$ from time step $t-1$ to t is computed based on the hidden state of the LSTM at time $t-1$.

Problem: Embeddings May Not be Indicative of Syntax

(He et al. 2018)

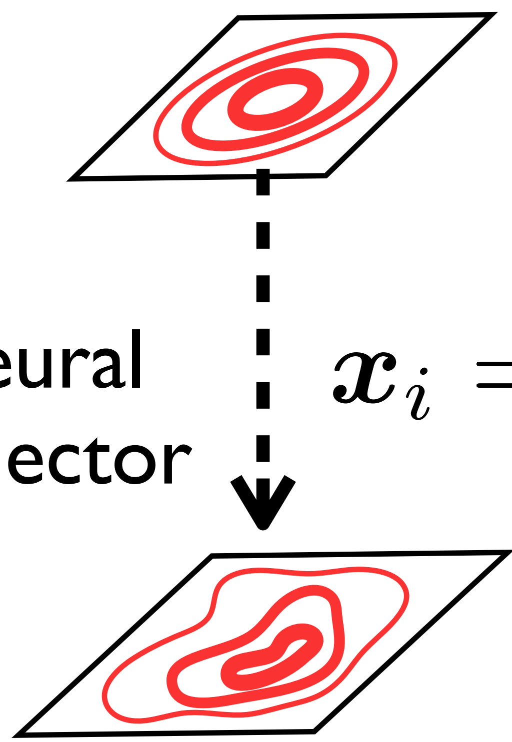


Learning POS Taggers w/ Latent Embeddings

(He et al. 2018)

$z_i \sim$ Markov Structure

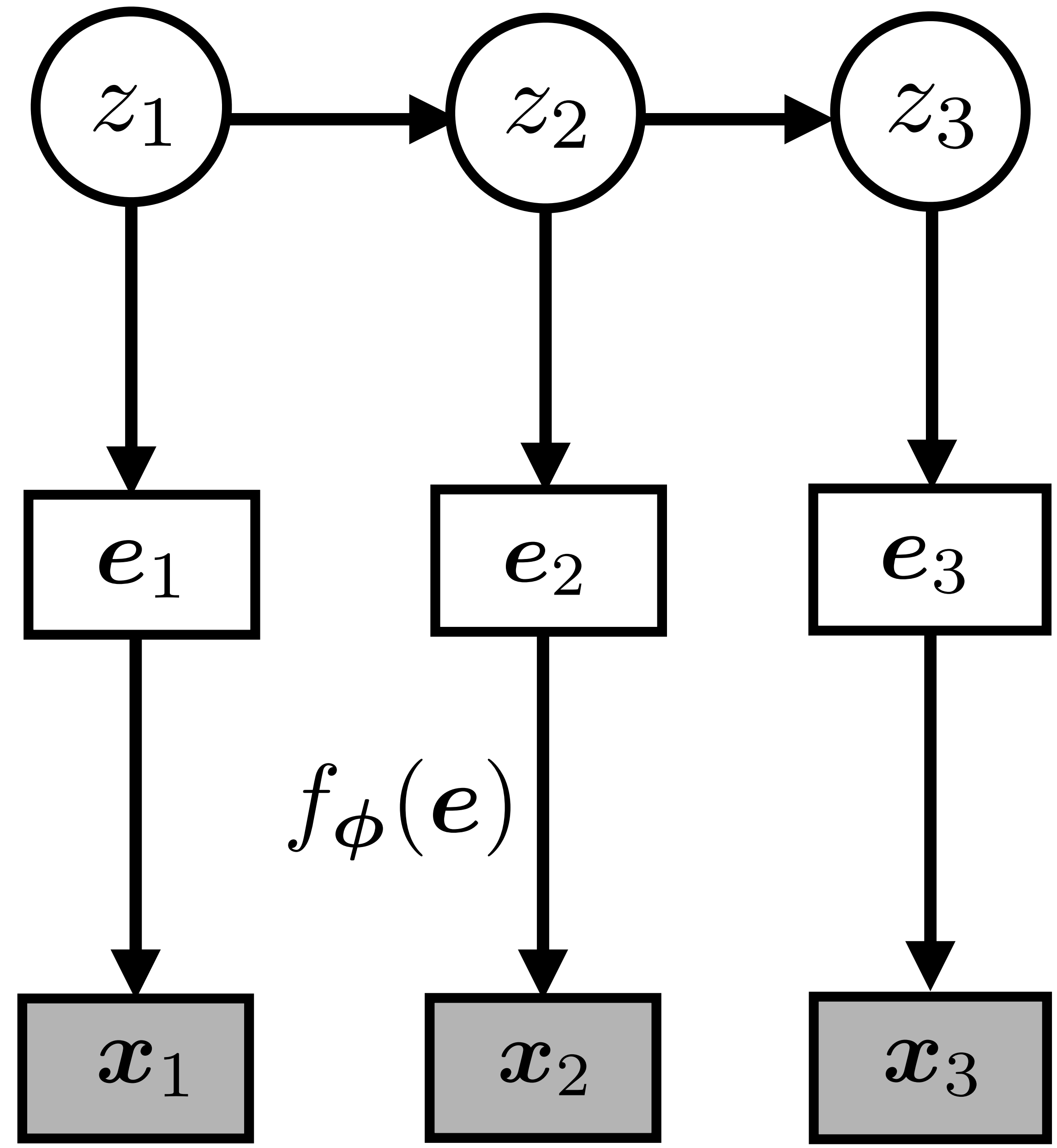
$\boldsymbol{e}_i \sim \mathcal{N}(\boldsymbol{\mu}_{z_i}, \boldsymbol{\Sigma}_{z_i})$



Neural Projector

$\boldsymbol{x}_i = f_\phi(\boldsymbol{e}_i)$

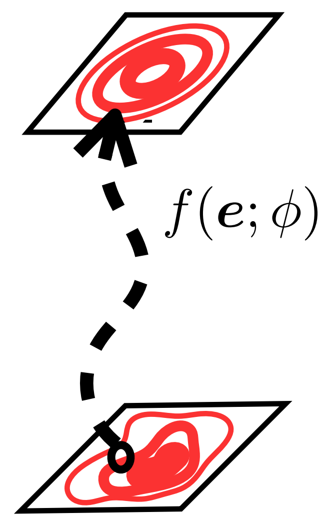
$\boldsymbol{x}_i \sim$ Point mass at $f_\phi(\boldsymbol{e}_i)$



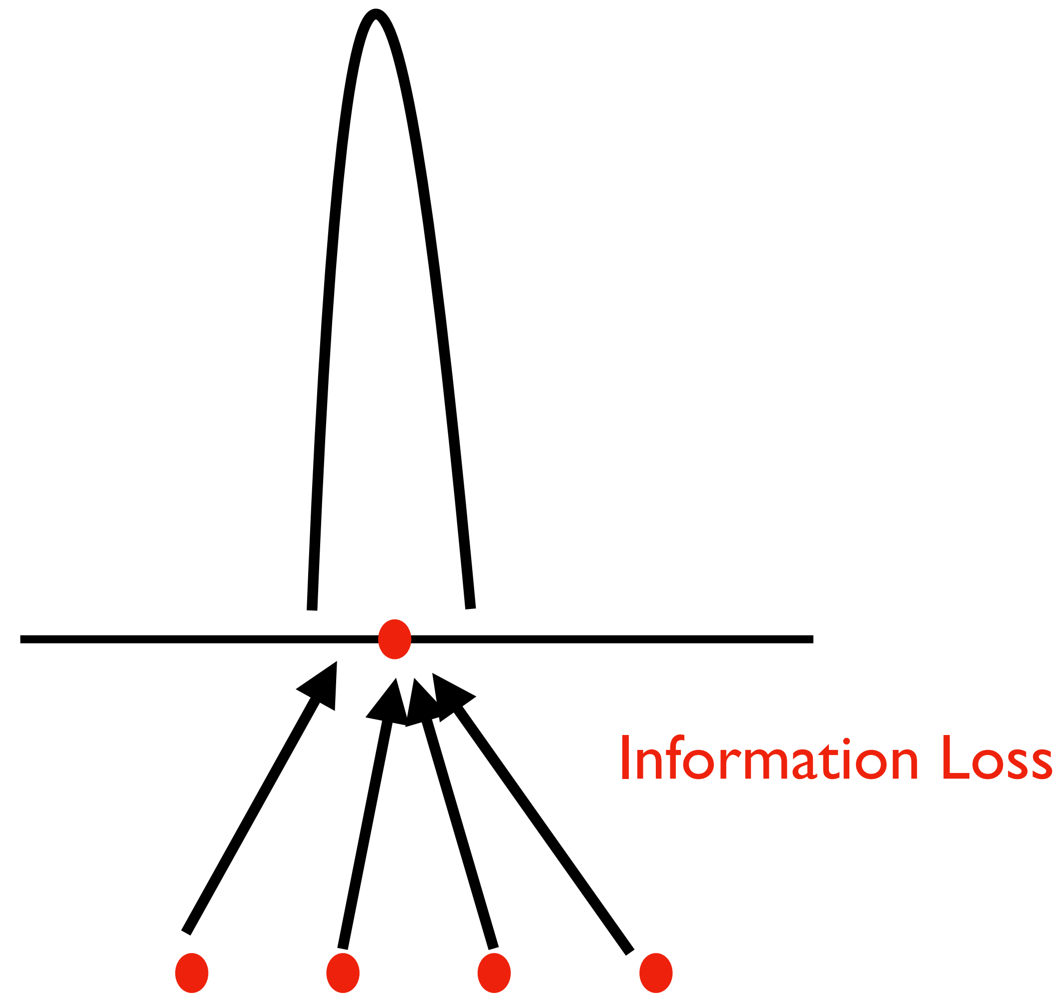
A Simpler Method: Map Directly to Space of Prior

Example of Markov prior

$$\max \ \log p_{\mathrm{GHMM}}(f_\phi(\boldsymbol{x}))$$

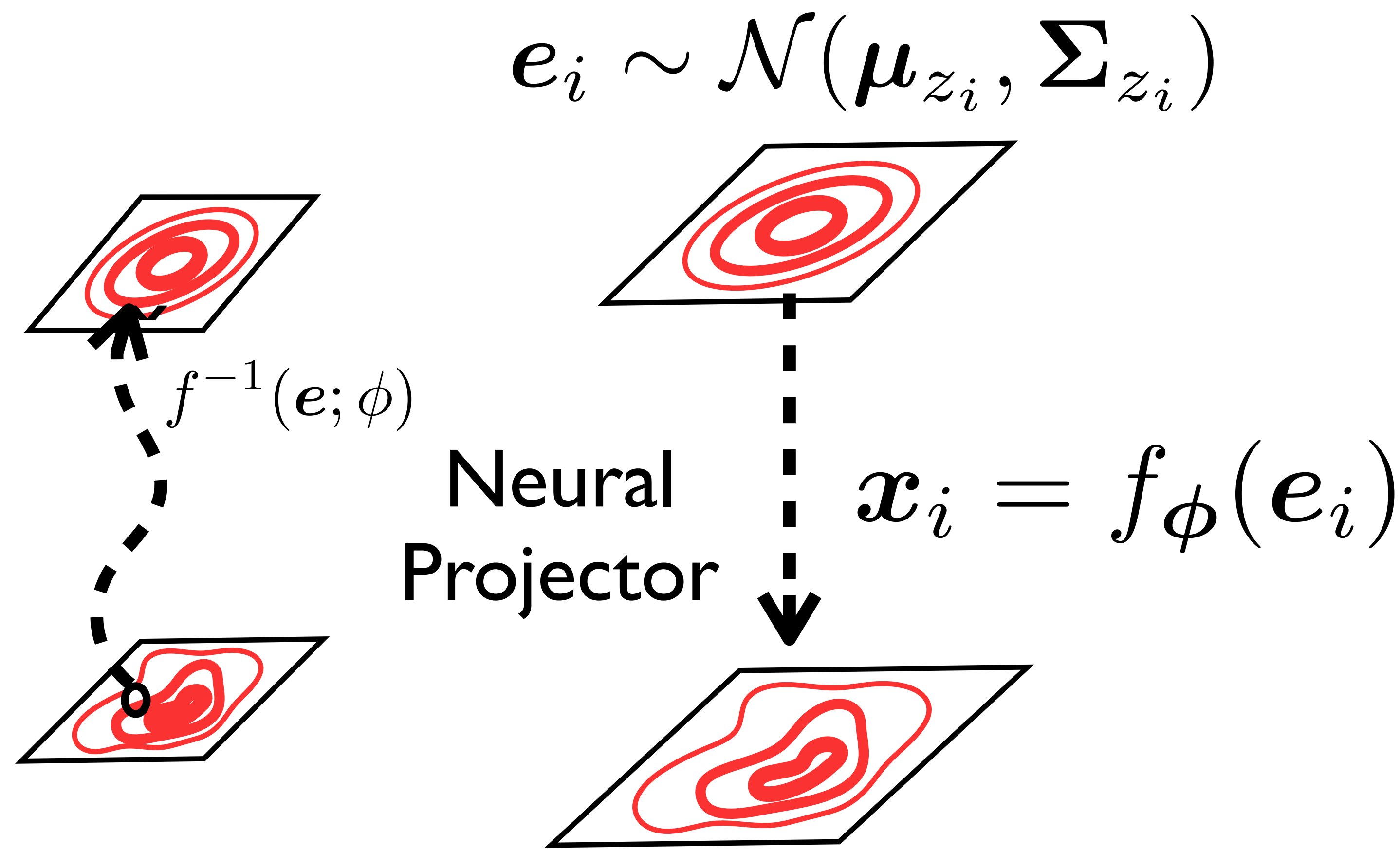


?



Normalizing Flow
(Rezende and Mohamed 2015)

- Basic idea: a way to map from one probability distribution to another in an invertible manner



- Advantage: optimizing probability can be shown to be possible by following equation

$$\log p(\boldsymbol{x}) = \log p_{\mathrm{GHMM}}(f_\phi^{-1}(\boldsymbol{x}))$$

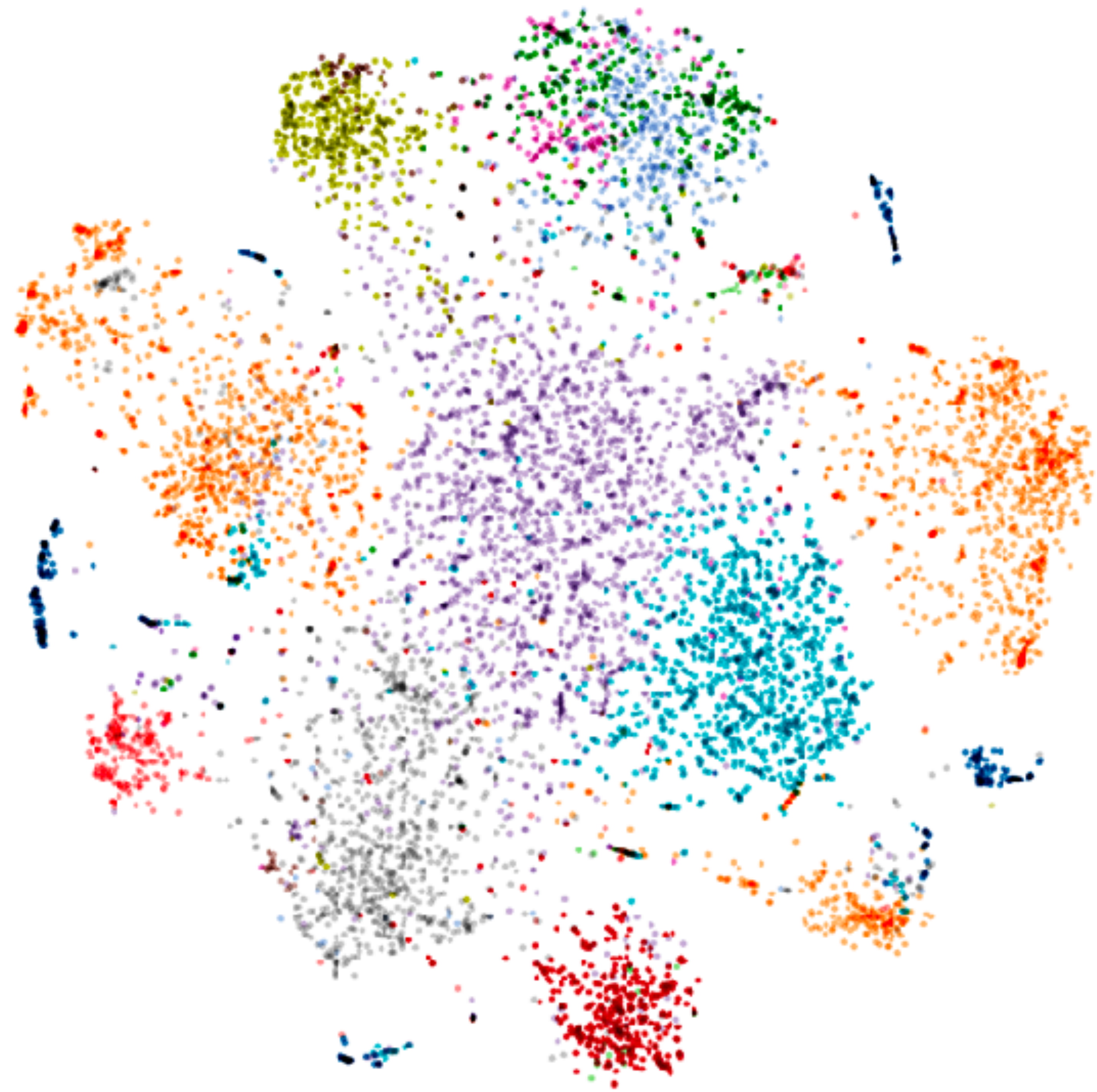
$$+ \sum \log \left| \det \frac{\partial f_\phi^{-1}}{\partial \boldsymbol{x}_i} \right|$$

$-\infty$ when f is not invertible

Results of Learning w/ HMM

(He et al. 2018)

adjective
adverb
noun singular
noun proper
noun plural
verb base
verb gerund
verb past tense
verb past participle
verb 3rd singular
cardinal number



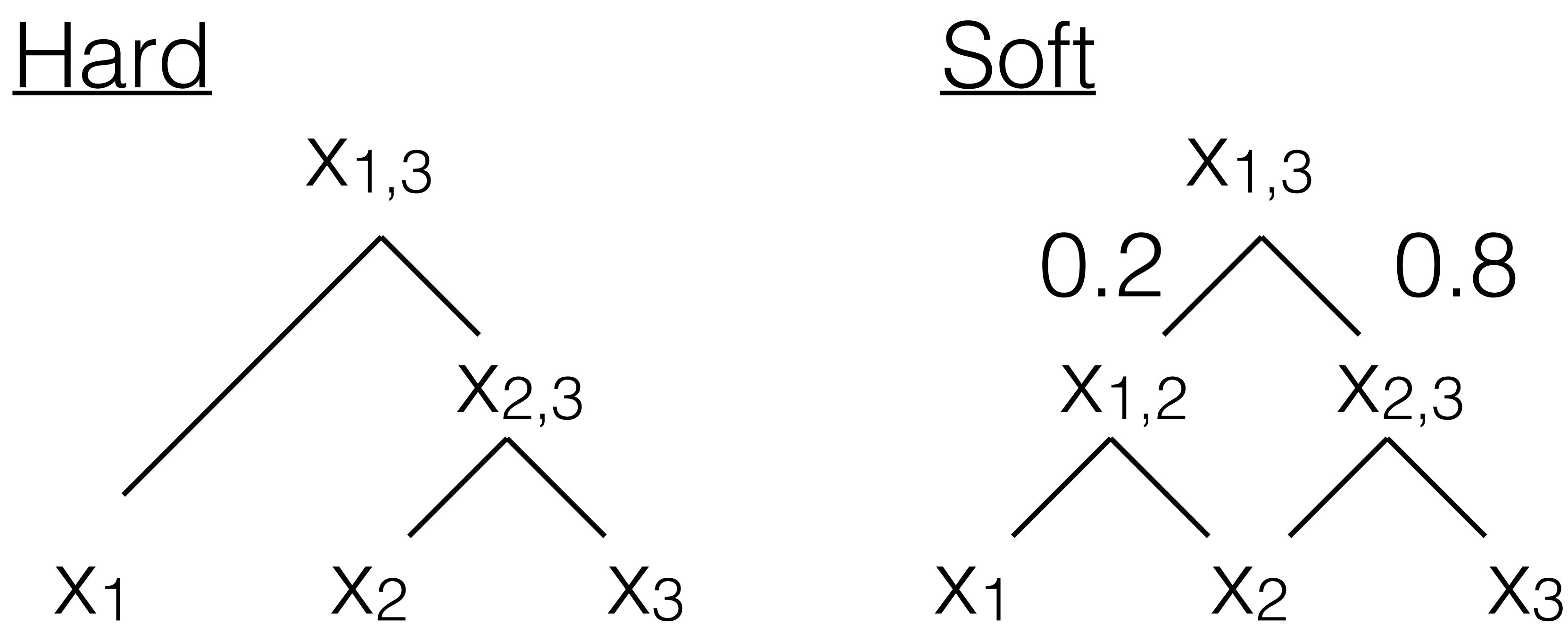
Cross-lingual Application of Unsupervised Models (He et al. 2019)

- Pre-train generative model in **supervised** fashion on high-resourced language
- **Fine-tune** the generative model to improve likelihood on a low-resource language
- **Improves accuracy** when transferring to distant languages
    - But not on similar languages -- maybe we need better generative models?

Unsupervised Phrase-structured Composition Functions

Soft vs. Hard Tree Structure

- Soft tree structure: use a differentiable gating function
- Hard tree structure: non-differentiable, but allows for more complicated composition methods



One Other Paradigm: Weak Supervision

- **Supervised:** given X,Y to model P(Y|X)

- **Unsupervised:** given X to model P(Y|X)

- **Weakly Supervised:** given X and V to model P(Y|X), under assumption that Y and V are correlated

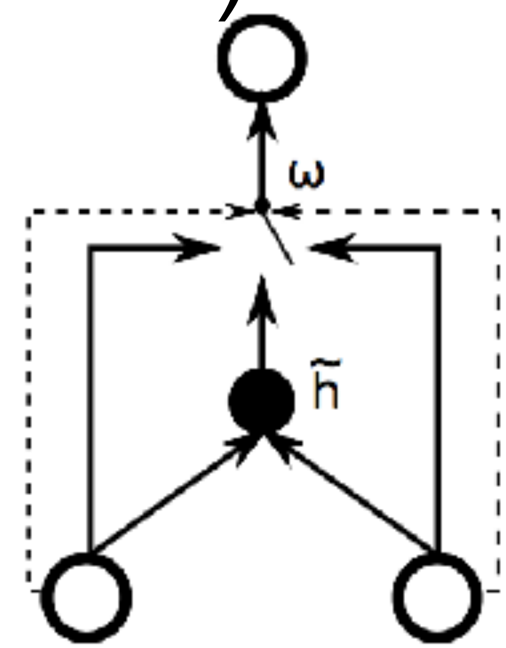
  - Note: different from multi-task or transfer learning because we are given no Y

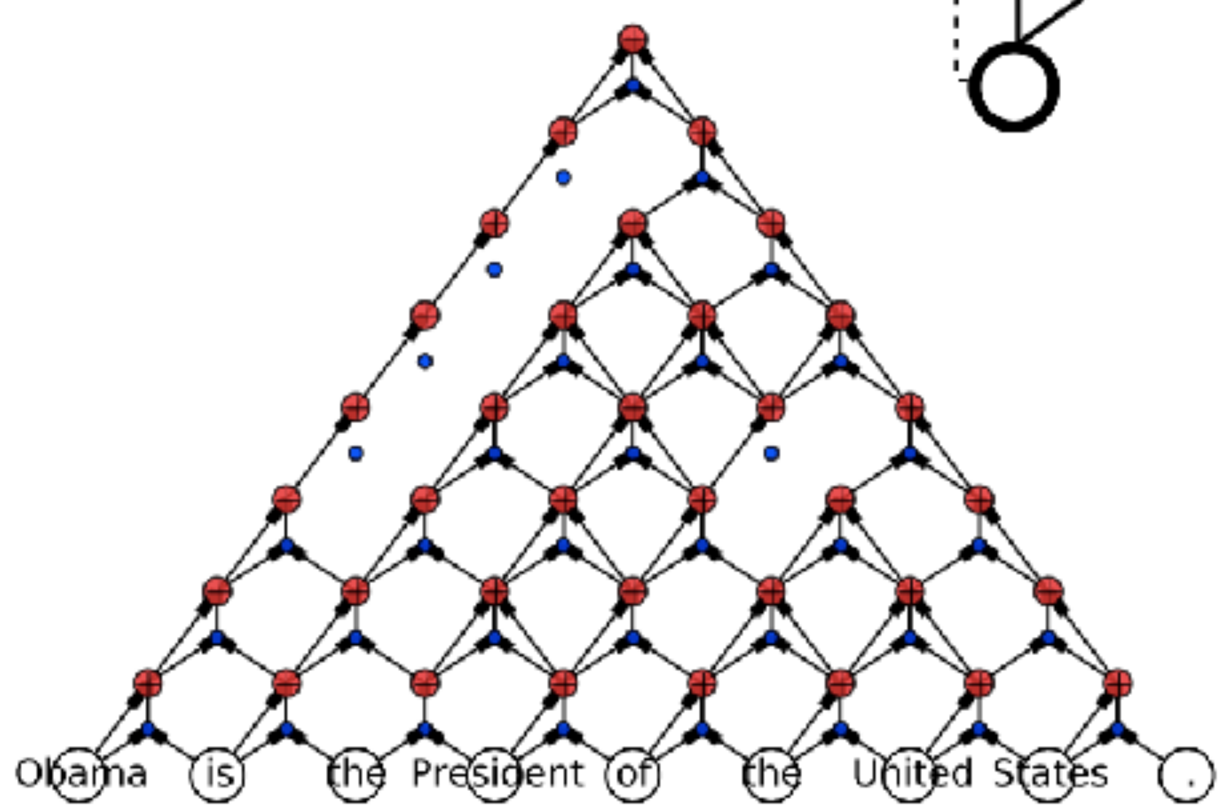
  - Note: different from supervised learning with latent variables, because we care about Y, not V

Gated Convolution

(Cho et al. 2014)

- Can choose whether to use left node, right node, or combination of both



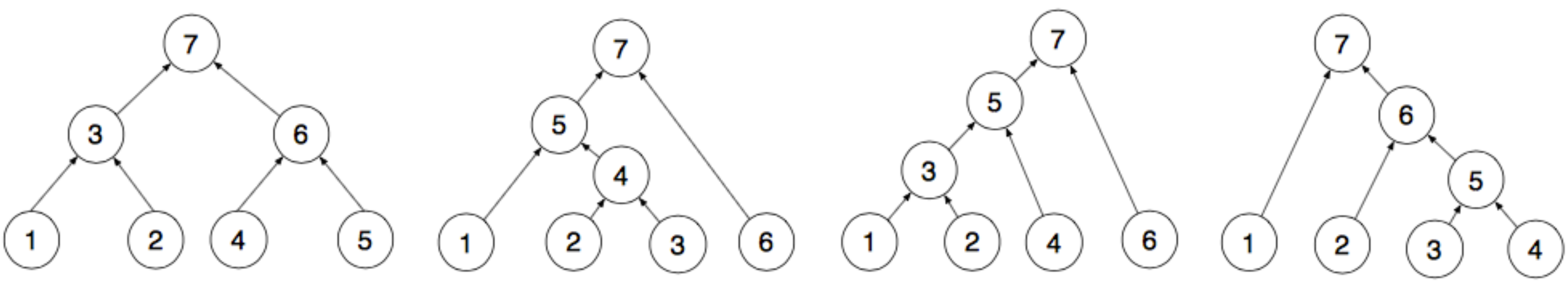


- Trained using MT loss

Learning with RL

(Yogatama et al. 2016)

- Intermediate tree-structured representation for language modeling
- Predict that tree using shift-reduce parsing, sentence representation composed in tree-structured manner
- Reinforcement learning with supervised loss, prediction loss



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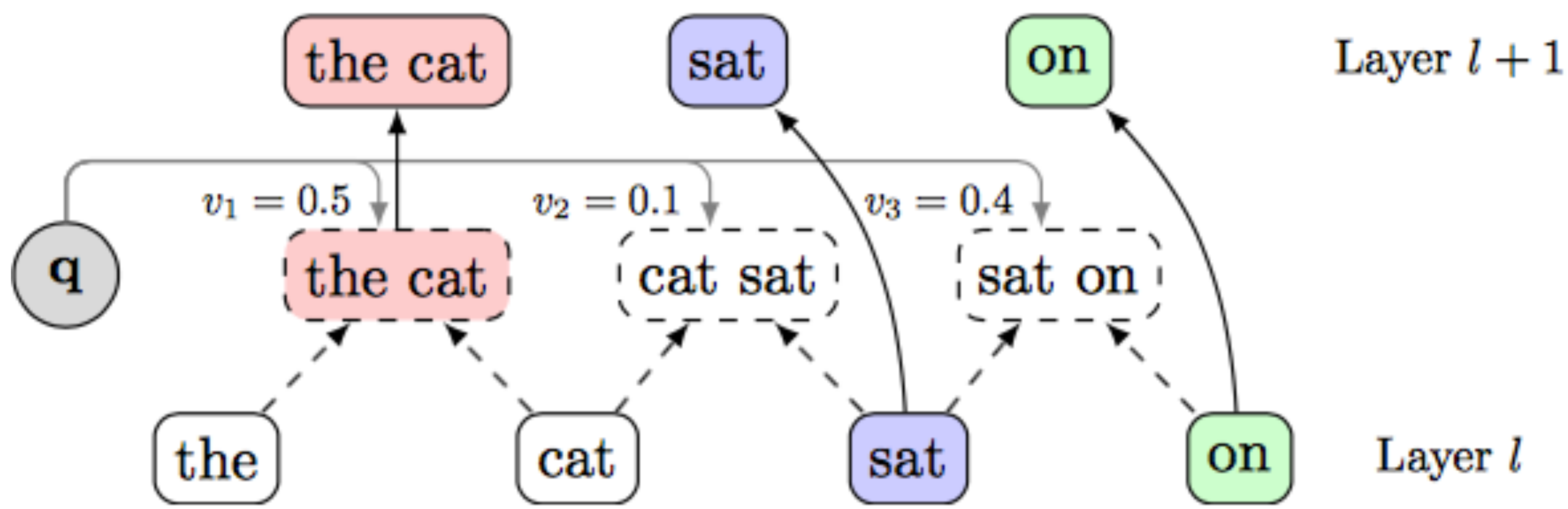
Learning w/ Layer-wise Reductions (Choi et al. 2017)

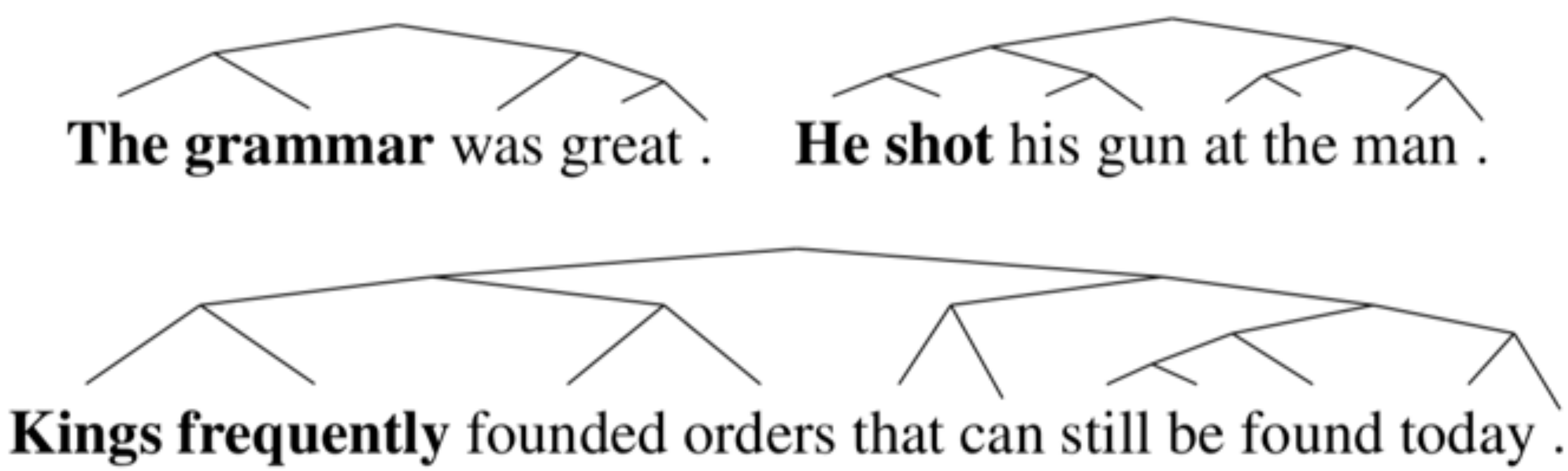
- Choose one parent at each layer, reducing size by one



- Train using Gumbel-straighthrough reparameterization trick
- Faster and more effective than RL?
- Williams et al. (2017) find that this gives less trivial trees as well

Difficulties in Learning Latent Structure
(Williams et al. 2018)

- Unfortunately, many models learn trivial structure...
    - e.g. balanced binary, left/right branching



- Why? One explanation: tension between (untrained) parser, and (untrained) downstream task model

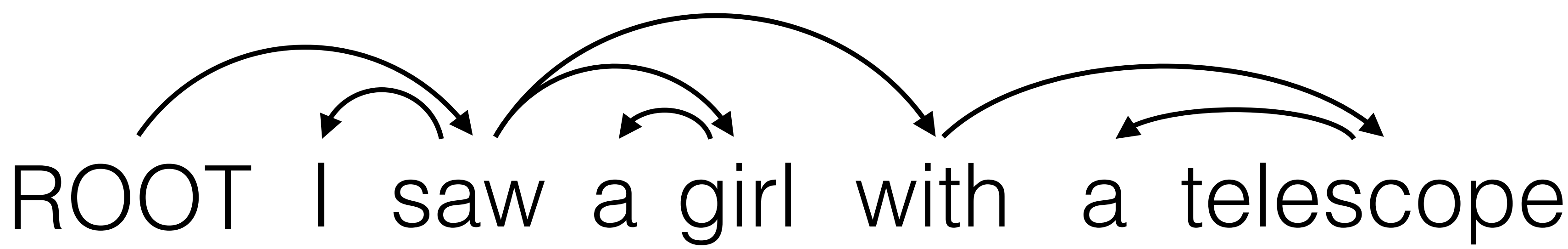
Learning Dependencies

Phrase Structure vs. Dependency Structure

- Previous methods attempt to learn representations of phrases in tree-structured manner
- We might also want to learn dependencies, that tell which words depend on others

Dependency Model w/ Valence (Klein and Manning 2004)

- Basic idea: top-down dependency based language model that generates left and right sides, then stops



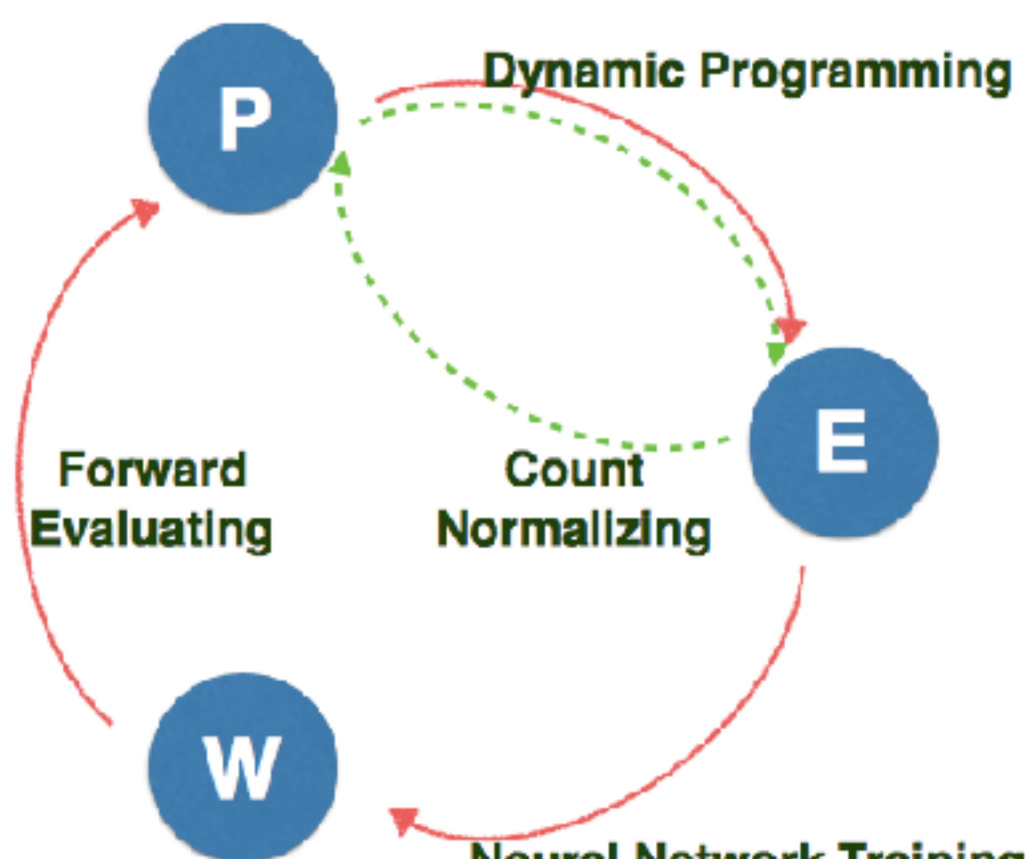
- For both the right and left side, calculate whether to continue generating words, and if yes generate

<u>e.g., a slightly simplified view for word "saw"</u>

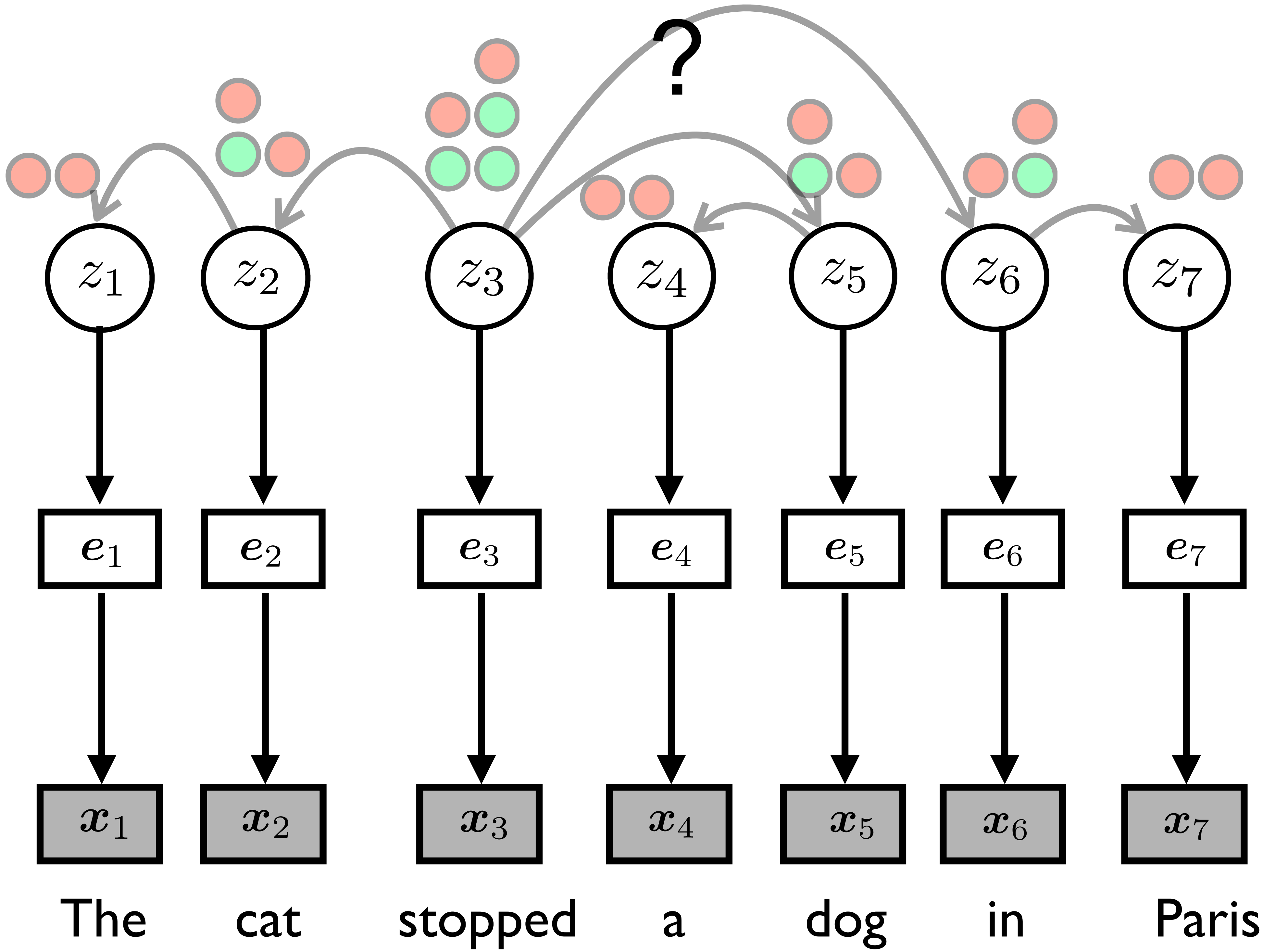
P_d(<cont> | saw, ←, false) * P_w(I | saw, ←, false) *
P_d(<stop> | saw, ←, true) *
P_d(<cont> | saw, →, false) * P_w(girl | saw, ←, false) *
P_d(<cont> | saw, →, true) * P_w(with | saw, ←, true) *
P_d(<stop> | saw, ←, true)

Unsupervised Dependency Induction w/ Neural Nets (Jiang et al. 2016)

- Simple: parameterize the decision with neural nets instead of with count-based distributions
- Like DMV, train with EM algorithm



Invertible Projections for DMV (He et al. 2018)



Learning Dependency Heads w/ Attention (Kuncoro et al. 2017)

- Given a phrase structure tree, what child is the head word, the most important word in the phrase?
- Idea: create a phrase composition function that uses attention: examine if attention weights follow heads defined by linguistics

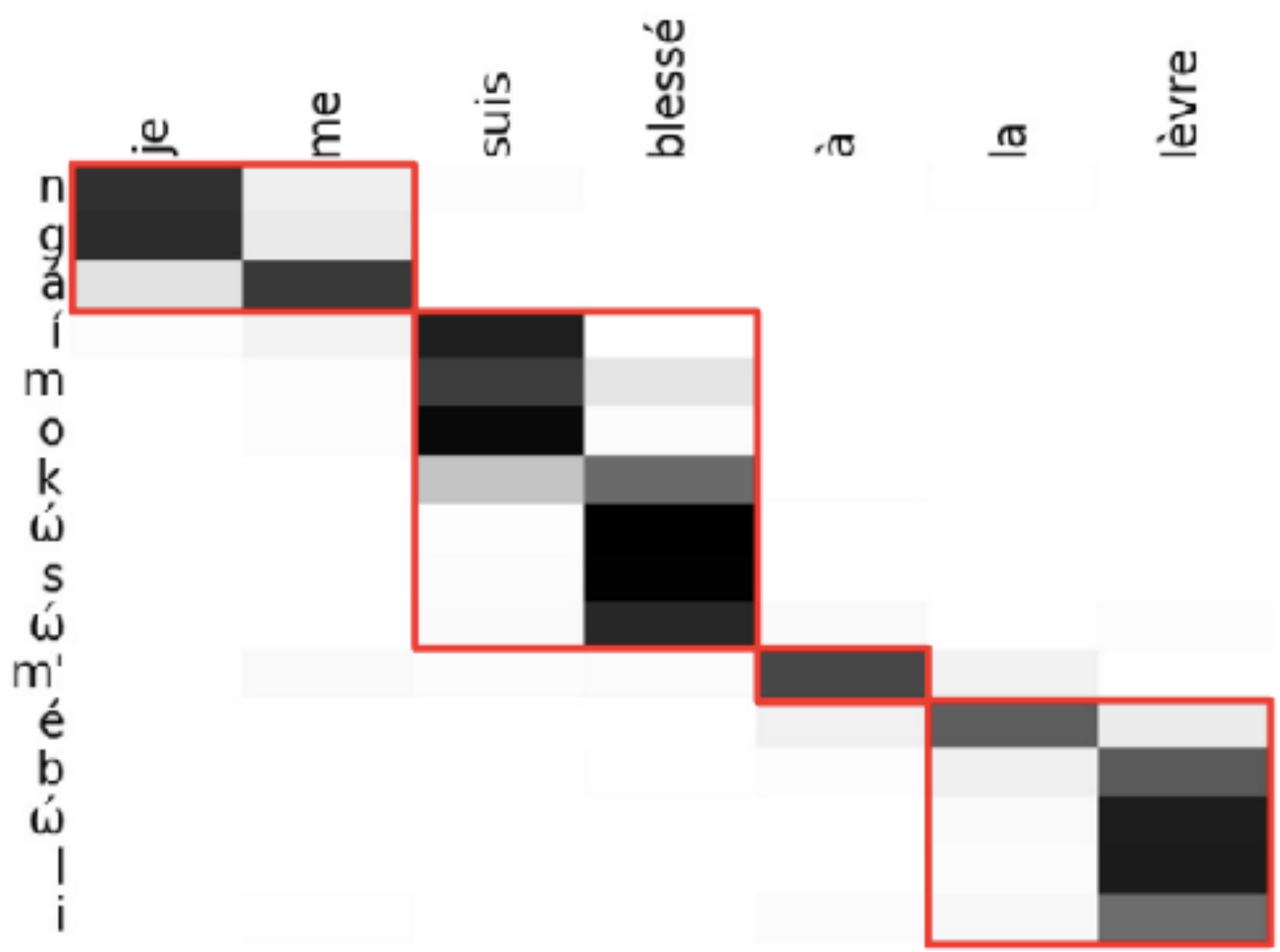
Noun phrases
Canadian (0.09) **Auto (0.31)** Workers (0.2) union (0.22) president (0.18)
no (0.29) major (0.05) **Eurobond (0.32)** or (0.01) foreign (0.01) bond (0.1) offerings (0.22)
Saatchi (0.12) client (0.14) Philips (0.21) Lighting (0.24) **Co. (0.29)**
nonperforming (0.18) commercial (0.23) **real (0.25)** estate (0.1) **assets (0.25)**
the (0.1) Jamaica (0.1) Tourist (0.03) Board (0.17) ad (0.20) **account (0.40)**
the (0.0) final (0.18) **hour (0.81)**
their (0.0) first (0.23) **test (0.77)**
Apple (0.62) , (0.02) Compaq (0.1) and (0.01) IBM (0.25)
both (0.02) stocks (0.03) and (0.06) **futures (0.88)**
NP (0.01) , (0.0) **and (0.98)** NP (0.01)

Verb phrases	Prepositional phrases
buying (0.31) and (0.25) selling (0.21) NP (0.23)	ADVP (0.14) **on (0.72)** NP (0.14)
ADVP (0.27) **show (0.29)** PRT (0.23) PP (0.21)	ADVP (0.05) **for (0.54)** NP (0.40)
pleaded (0.48) ADJP (0.23) PP (0.15) PP (0.08) PP (0.06)	ADVP (0.02) **because (0.73)** of (0.18) NP (0.07)
received (0.33) PP (0.18) NP (0.32) PP (0.17)	such (0.31) **as (0.65)** NP (0.04)
cut (0.27) **NP (0.37)** PP (0.22) PP (0.14)	from (0.39) **NP (0.49)** PP (0.12)
to (0.99) VP (0.01)	**of (0.97)** NP (0.03)
were (0.77) n't (0.22) VP (0.01)	**in (0.93)** NP (0.07)
did (0.39) **n't (0.60)** VP (0.01)	**by (0.96)** S (0.04)
handle (0.09) **NP (0.91)**	**at (0.99)** NP (0.01)
VP (0.15) **and (0.83)** VP 0.02)	NP (0.1) **after (0.83)** NP (0.06)

Other Examples

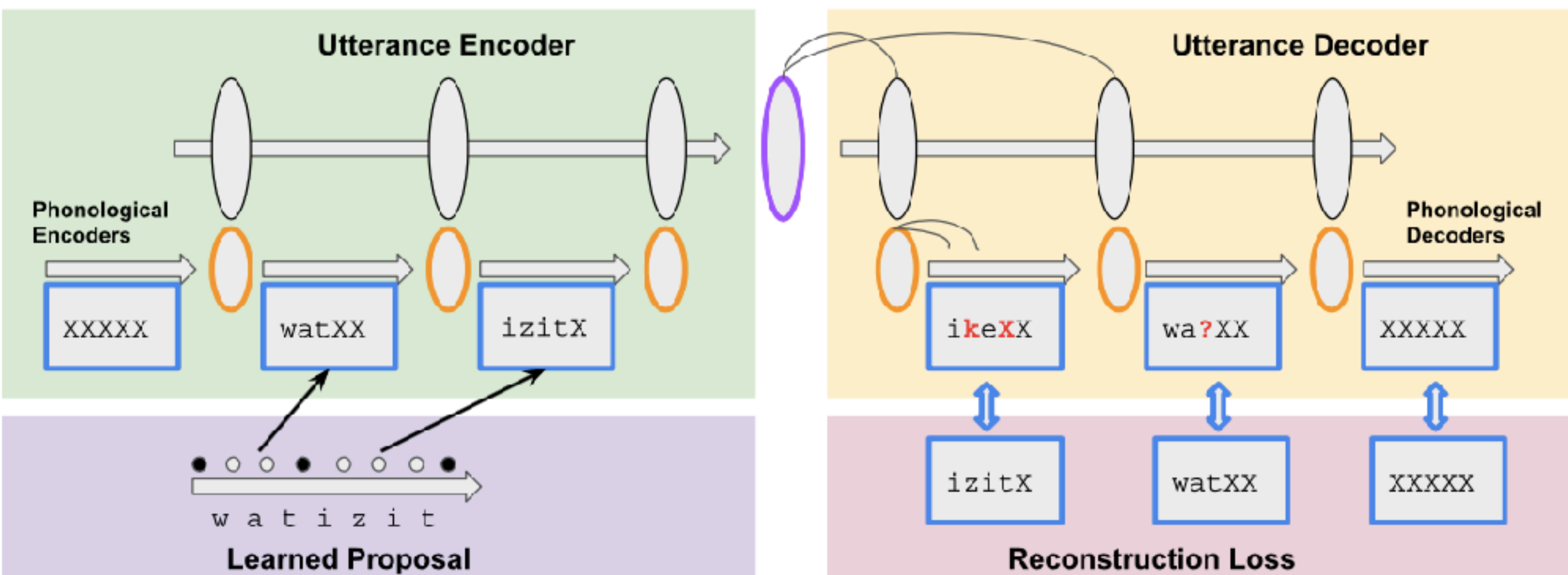
Learning about Word Segmentation from Attention (Boito et al. 2017)

- We want to learn word segmentation in an unsegmented language
- Simple idea: we can inspect the attention matrices from a neural MT system to extract words



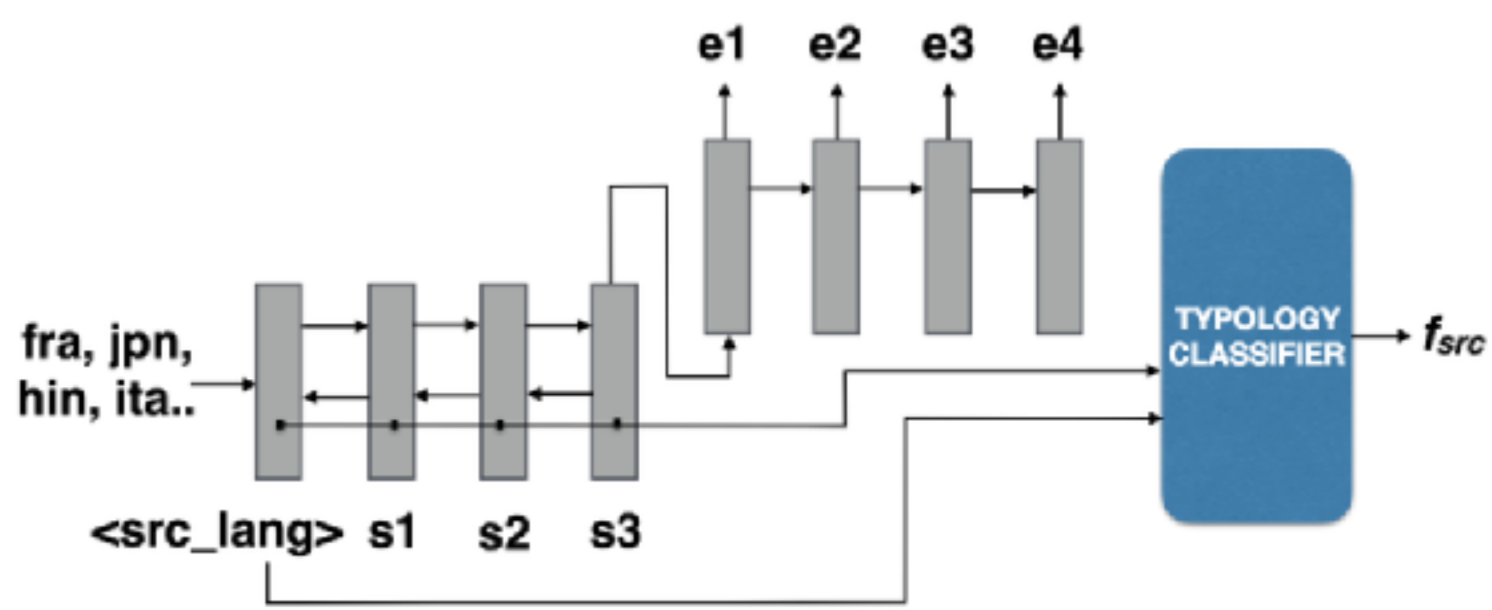
Learning Segmentations w/ Reconstruction Loss (Elsner and Shain 2017)

- Learn segmentations of speech/text that allow for easy re-construction of the original
- Idea: consistent segmentation should result in easier-to-reconstruct segments
- Train segmentation using policy gradient



Learning Language-level Features (Malaviya et al. 2017)

- All previous work learned features of a single sentence
- Can we learn *features of the whole language*? e.g. Typology: what is the canonical word order, etc.
- A simple method: train a neural MT system on 1017 languages, and extract its representations



Questions?