# Learning about Language with Normalizing Flows

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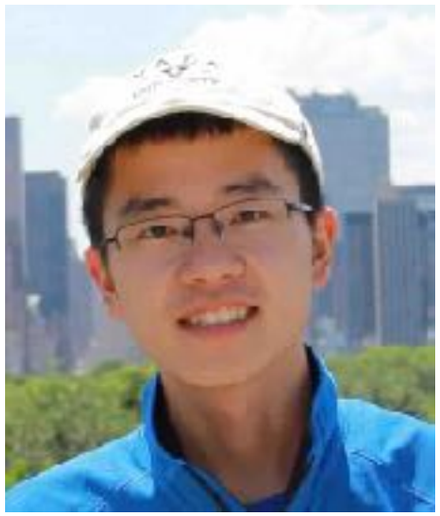
Chunting Zhou Junxian He Xuezhe Ma


Di Wang, Daniel Spokoyny, Xian Li, Taylor Berg-Kirkpatrick, Eduard Hovy

Language Technologies Institute

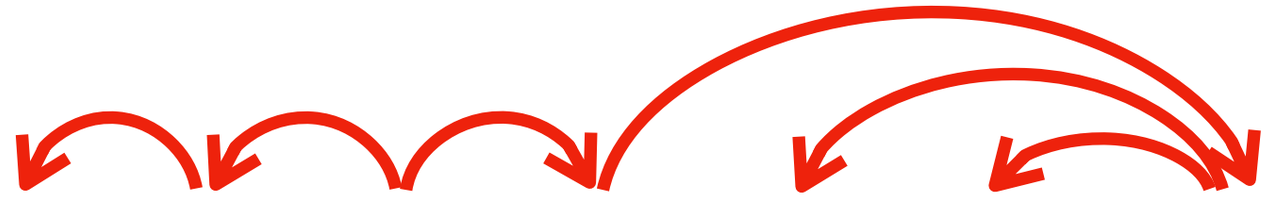
# Learning about Language?

- **Syntactic structure**

The cat sat on a green wall

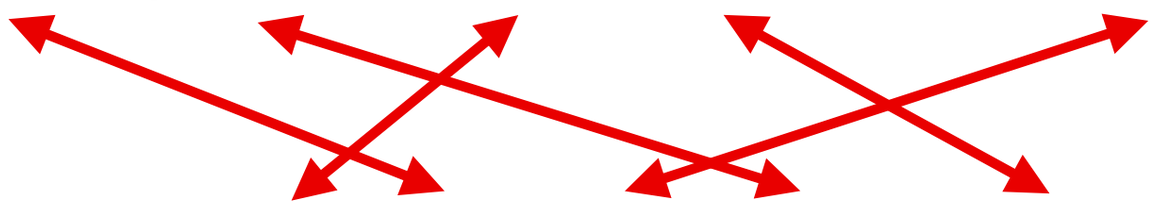
Parts-of-speech: DT NN VBD IN DT JJ NN

Dependency:



- **Cross-lingual correspondences**

a cat green on sat the wall



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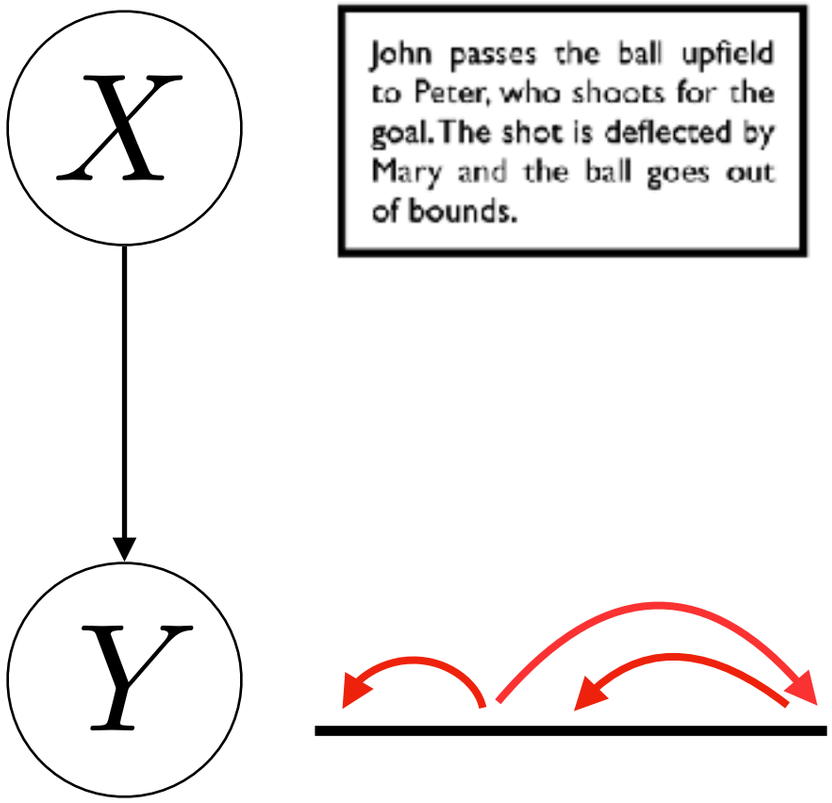
# Supervised Approaches



# Supervised Approaches

## Supervised Learning

$X$ $\theta$ $Y$

John passes the ball upfield to Peter, who shoots for the goal. The shot is deflected by Mary and the ball goes out of bounds.

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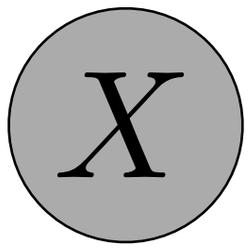


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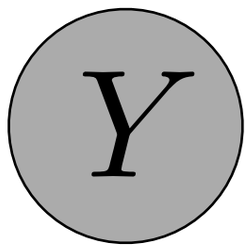
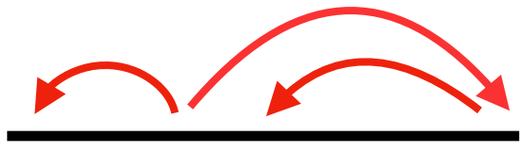
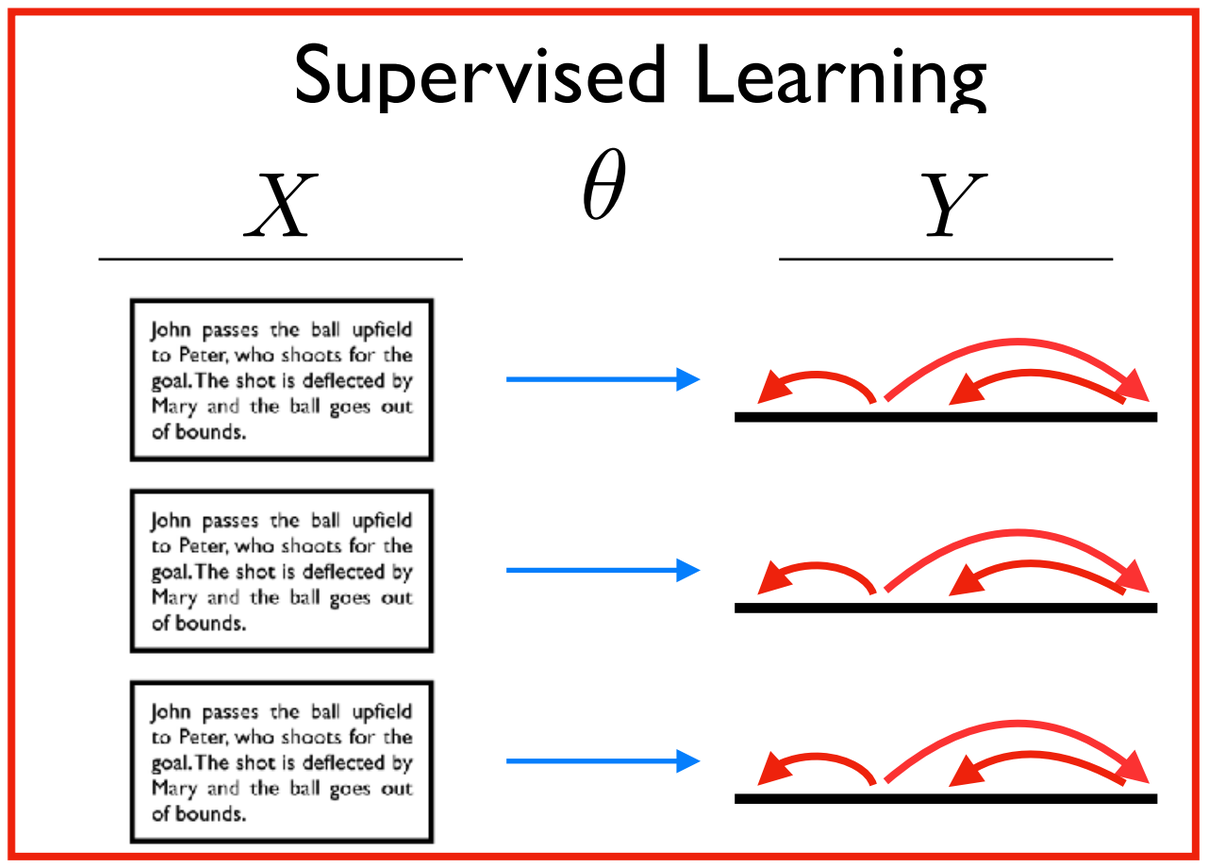
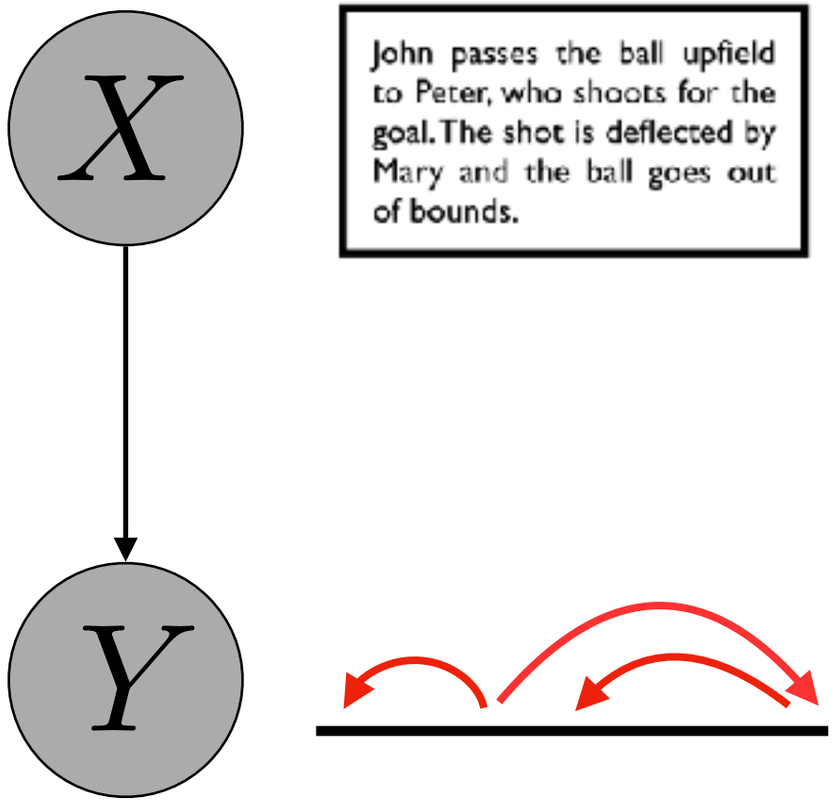


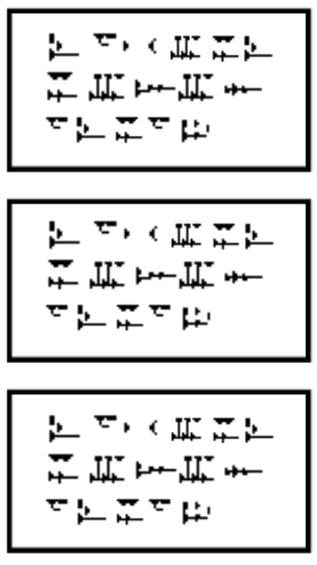
# Supervised Approaches



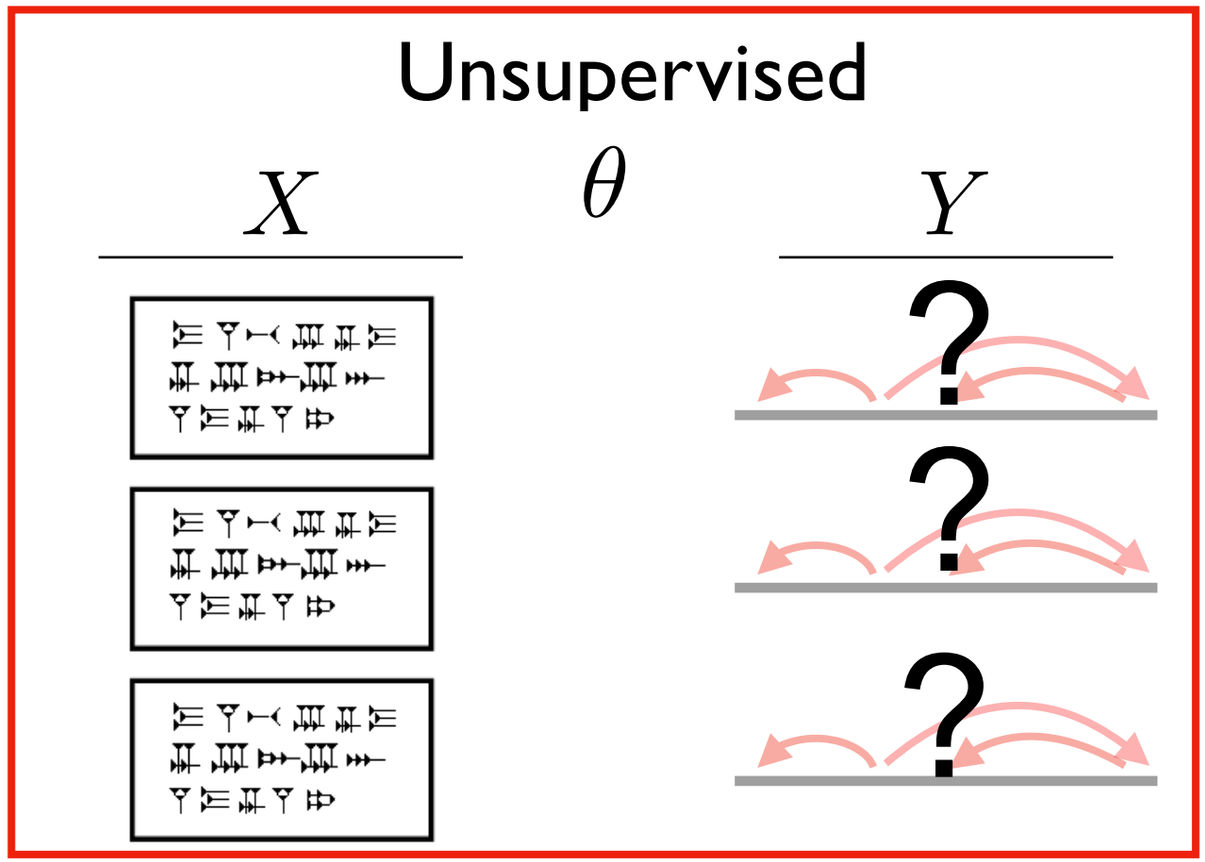
# Unsupervised Approaches

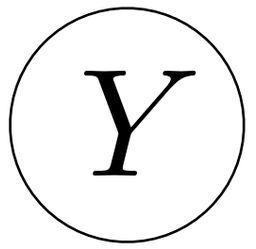
$$X$$

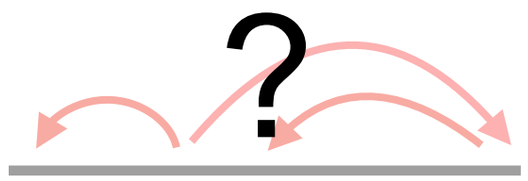


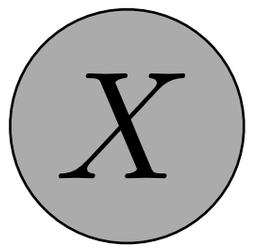
- Learning language models P(X)
- Learning continuous features from language models (e.g. word2vec, skipthought, BERT)
- But how do we turn this into **interpretable structure**?
- How do we do it while **taking advantage of continuous features**?

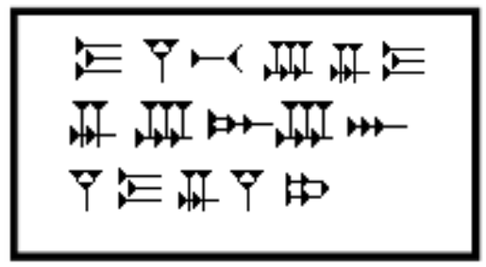
# Latent Variable Approaches



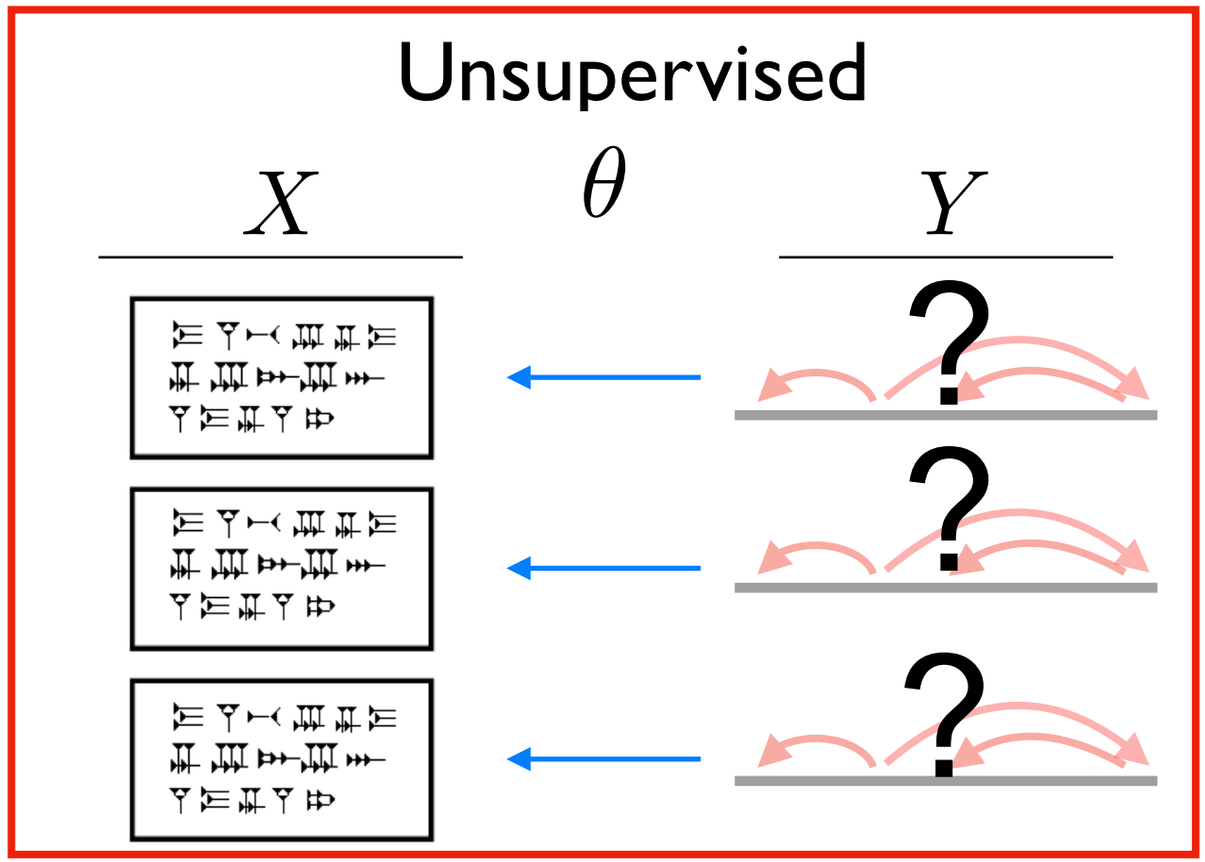



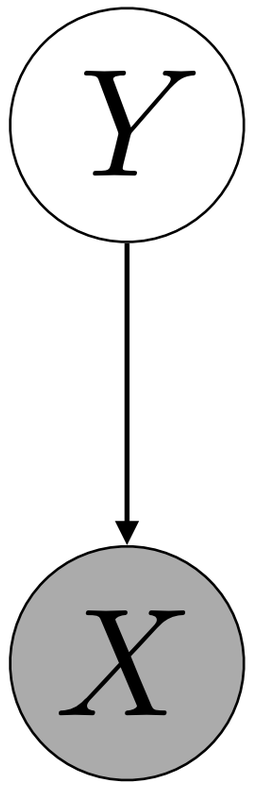



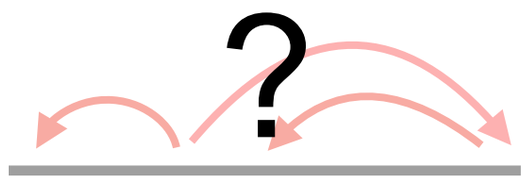



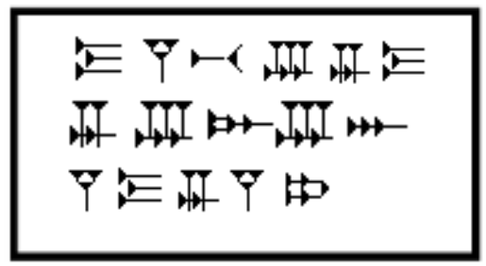



# Latent Variable Approaches



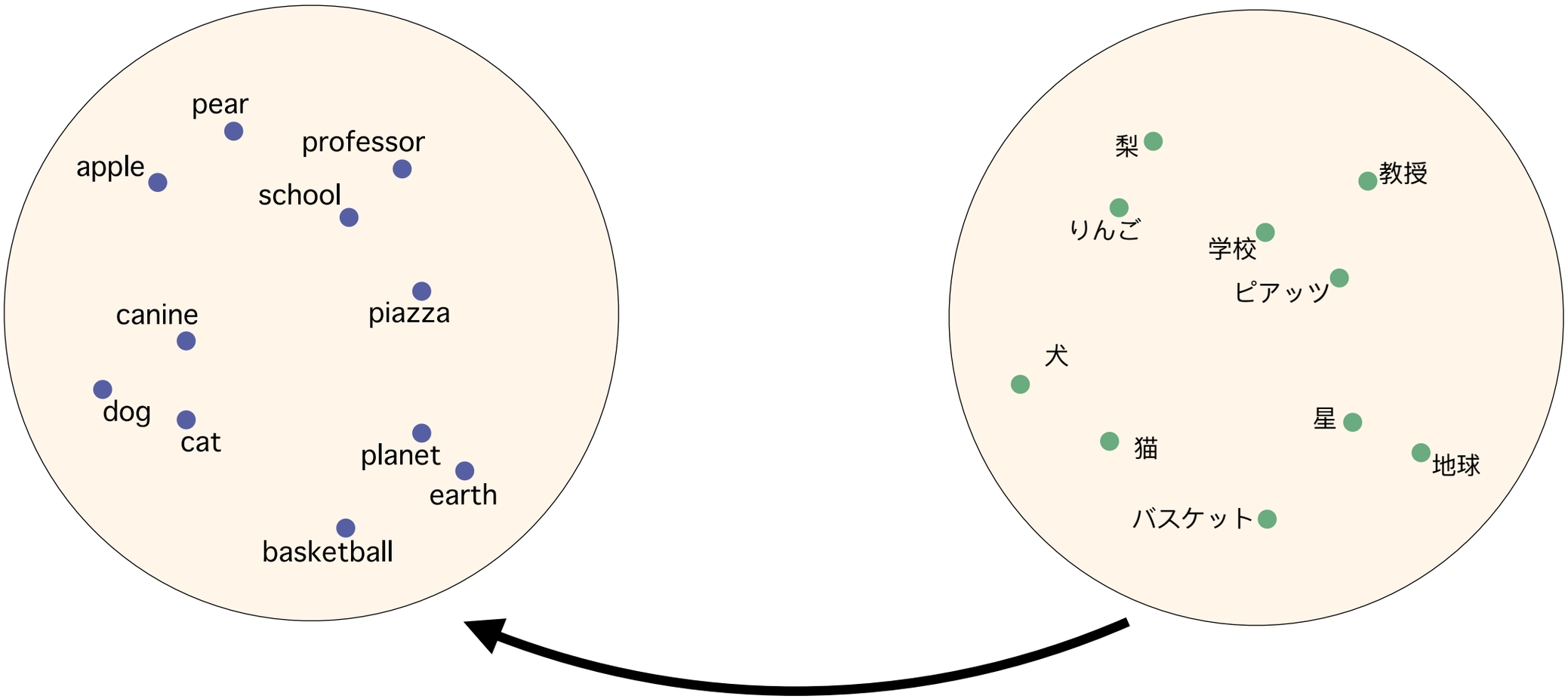



# Density Matching for Bilingual Word Embedding

Chunting Zhou, Xuezhe Ma, Di Wang, Graham Neubig

(NAACL 2019)

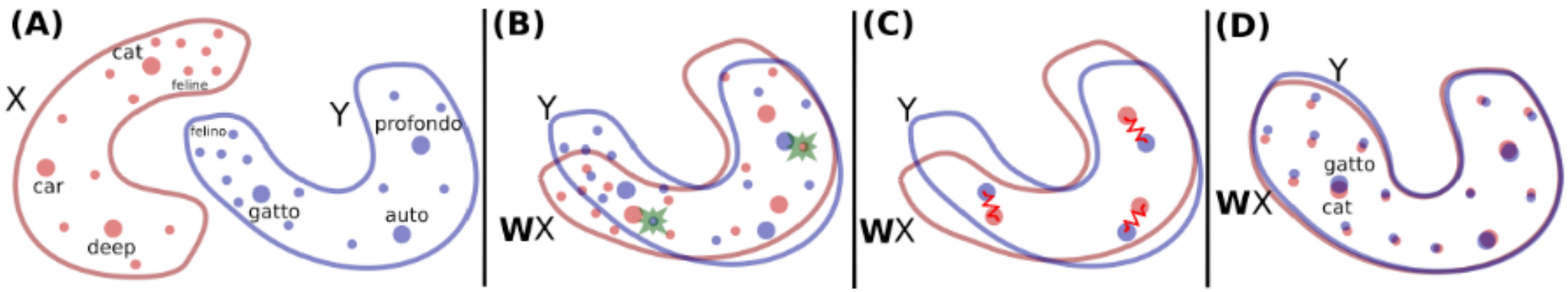
# Bilingual Word Embedding




- Map word embeddings from different languages into a single vector space
  - -Cross-lingual transfer
  - -Cross-lingual NLP tasks

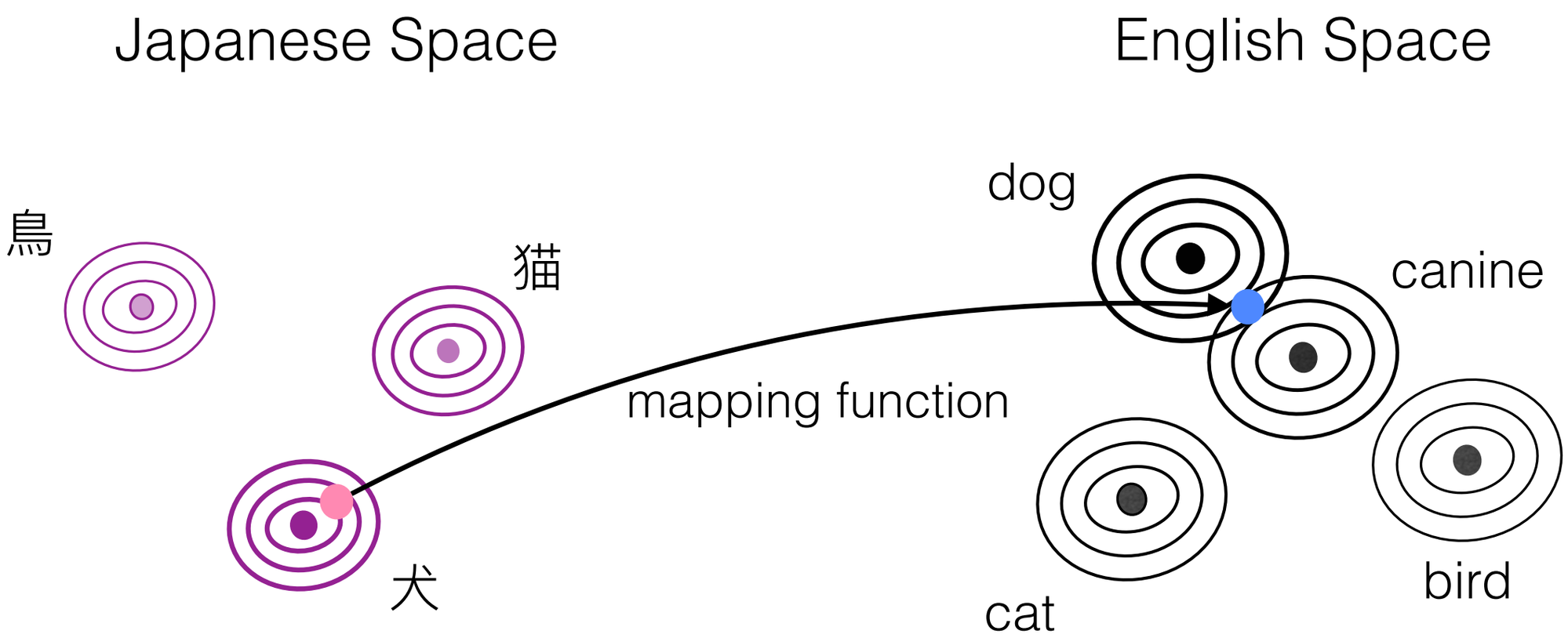
# Previous Work on Unsupervised BWE

- Unsupervised methods of minimization some form of distance between distributions of discrete vector sets:




- No direct probabilistic interpretation, not a "typical" unsupervised generative model

# Density Mapping for Bilingual Word Embedding (DeMa-BWE)



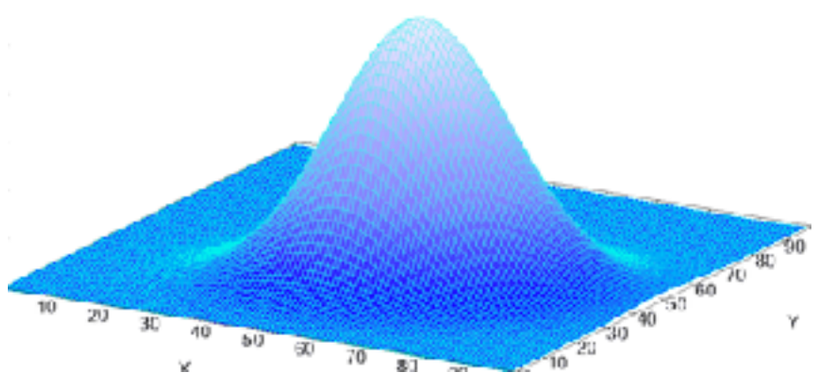

- Mapping function is learned with **normalizing flow**

# Normalizing Flows

$$X = f_\theta^{-1}(Z)$$

$$Z = f_\theta(X)$$

$$X \sim P(X)$$



$$Z \sim N(0, I)$$

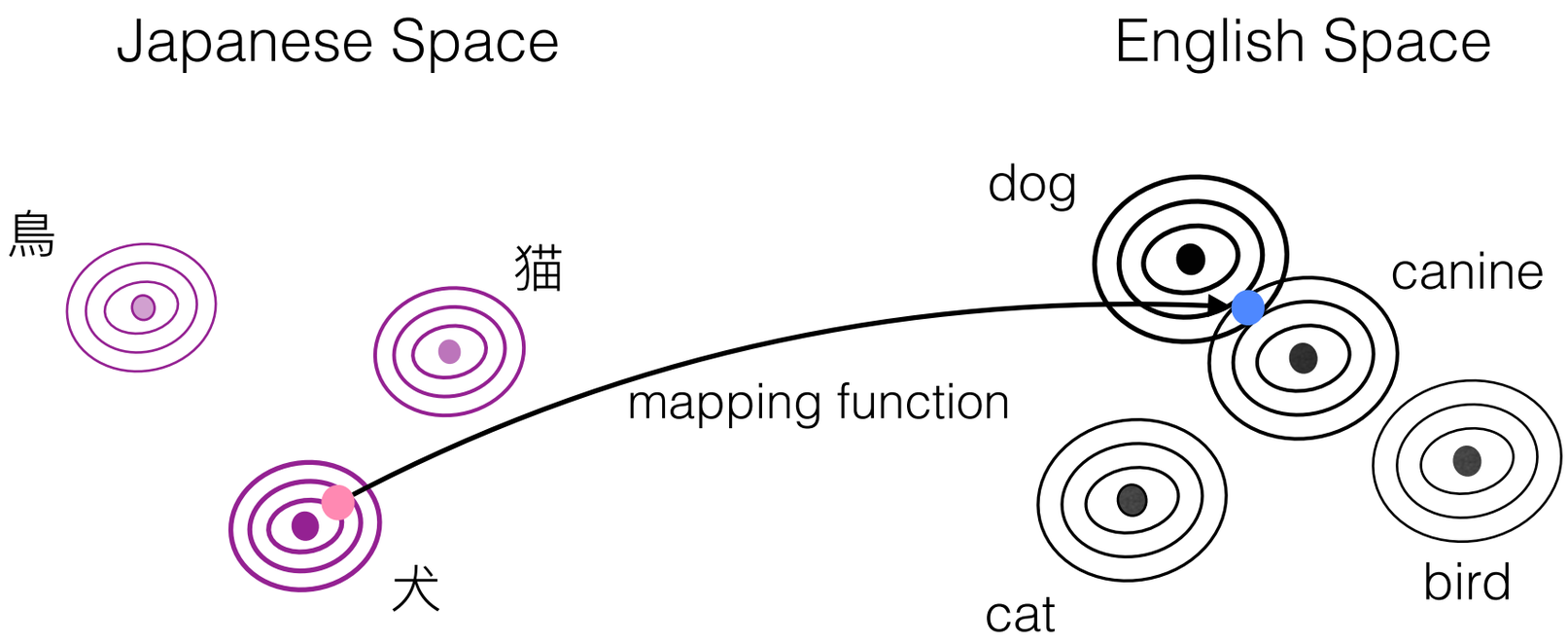
**Change of variable formula:**

$$p_\theta(x) = p_Z(f_\theta(x)) \left| \det\left(\frac{\partial f_\theta(x)}{\partial x}\right) \right|$$

Intuitively, prevents degenerative mapping of everything to zero vector

**Normalizing Flow:** A series of such invertible transformations $f$

# DeMa-BWE: Preliminaries




Notations:

$\mathbf{x} \in \mathbb{R}^d, \quad \mathbf{y} \in \mathbb{R}^d$ : denote vectors in the src and tgt embedding space

$x_i, \quad y_j$ : denote an actual word in src and tgt vocabularies

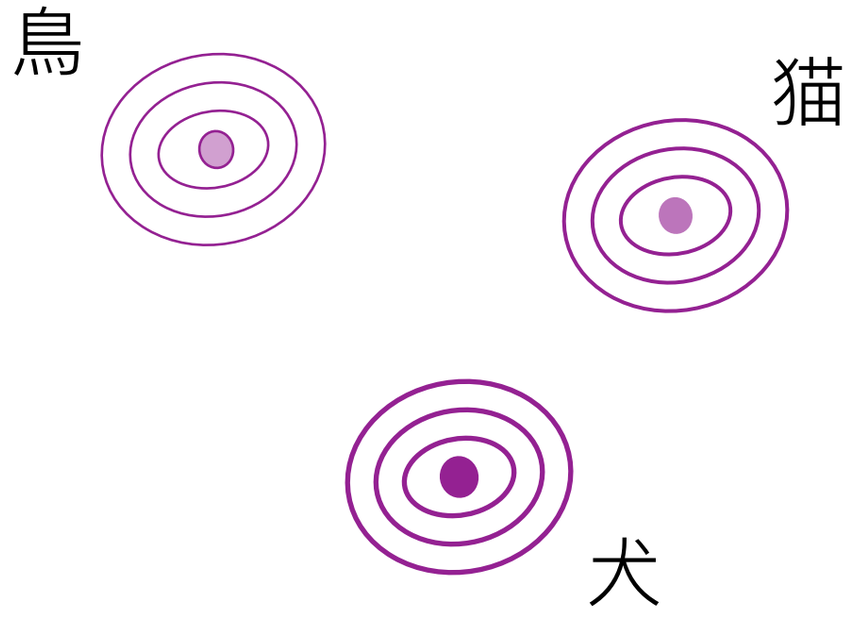
$f_{xy}, \quad f_{yx}$ : denote src->tgt, and tgt-src mapping functions

# Prior Distribution

- Assumption on the monolingual word embedding space: Gaussian mixture model

$$p(\mathbf{x}) = \sum_{i \in \{1,\ldots,N_x\}} \pi(x_i)\tilde{p}(\mathbf{x}|x_i)$$

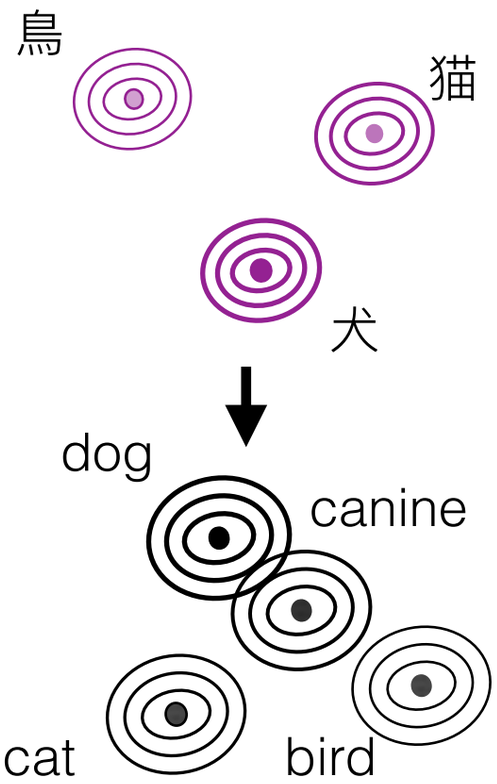
$$\tilde{p}(\mathbf{x}|x_i) = \mathcal{N}(\mathbf{x}|\mathbf{x}_i, \sigma_x^2\mathbf{I})$$



# DeMa-BWE: Density Matching

- Sampling a continuous vector from the GMM

$$x_i \sim \pi(x_i) \qquad \mathbf{x} \sim \tilde{p}(\mathbf{x}|x_i)$$




- Apply the mapping function $f_{xy}$ to obtain the transformed vector in the target space.

$$f_{xy}(\cdot) = \mathbf{W}_{xy}.$$

- Computing the density of x in the mapped target space

$$\log p(\mathbf{x}; \mathbf{W}_{xy}) = \log p(\mathbf{y}) + \log \left|\det(\mathbf{W}_{xy})\right|$$

- Objective: $\text{minimize: } \mathrm{KL}(p(\mathbf{x})||p(\mathbf{x}; \mathbf{W}_{xy}))$

$$\mathcal{L}_{xy} = \mathrm{E}_{\mathbf{x}\sim p(\mathbf{x})}[\log p(\mathbf{y}) + \log \left|\det(\mathbf{W}_{xy})\right|]$$

# Method Details

- **Weak Orthogonality Constraint:** Try to make sure that the transformation is close to orthogonal

$$\mathcal{L}_{bt} = \mathrm{E}_{x_i \sim \pi(x_i), \mathbf{x} \sim \tilde{p}(\mathbf{x}|x_i)} \left[ g(\mathbf{W}_{yx}\mathbf{W}_{xy}\mathbf{x}, \mathbf{x}) \right] + \mathrm{E}_{y_j \sim \pi(y_j), \mathbf{y} \sim \tilde{p}(\mathbf{y}|x_j)} \left[ g(\mathbf{W}_{xy}\mathbf{W}_{yx}\mathbf{y}, \mathbf{y}) \right]$$

- **Weak Supervision w/ Identical Strings:** Take advantage of the fact that identical strings are usually the same word in both languages

$$\mathcal{L}_{sup} = \sum_{v \in \mathcal{W}_{id}} g(\mathbf{v}_x \mathbf{W}_{xy}^T, \mathbf{v}_y) + g(\mathbf{v}_y \mathbf{W}_{yx}^T, \mathbf{v}_x)$$

- **Alignment Selection Methods:** Use cross-domain similarity local scaling (CSLS)

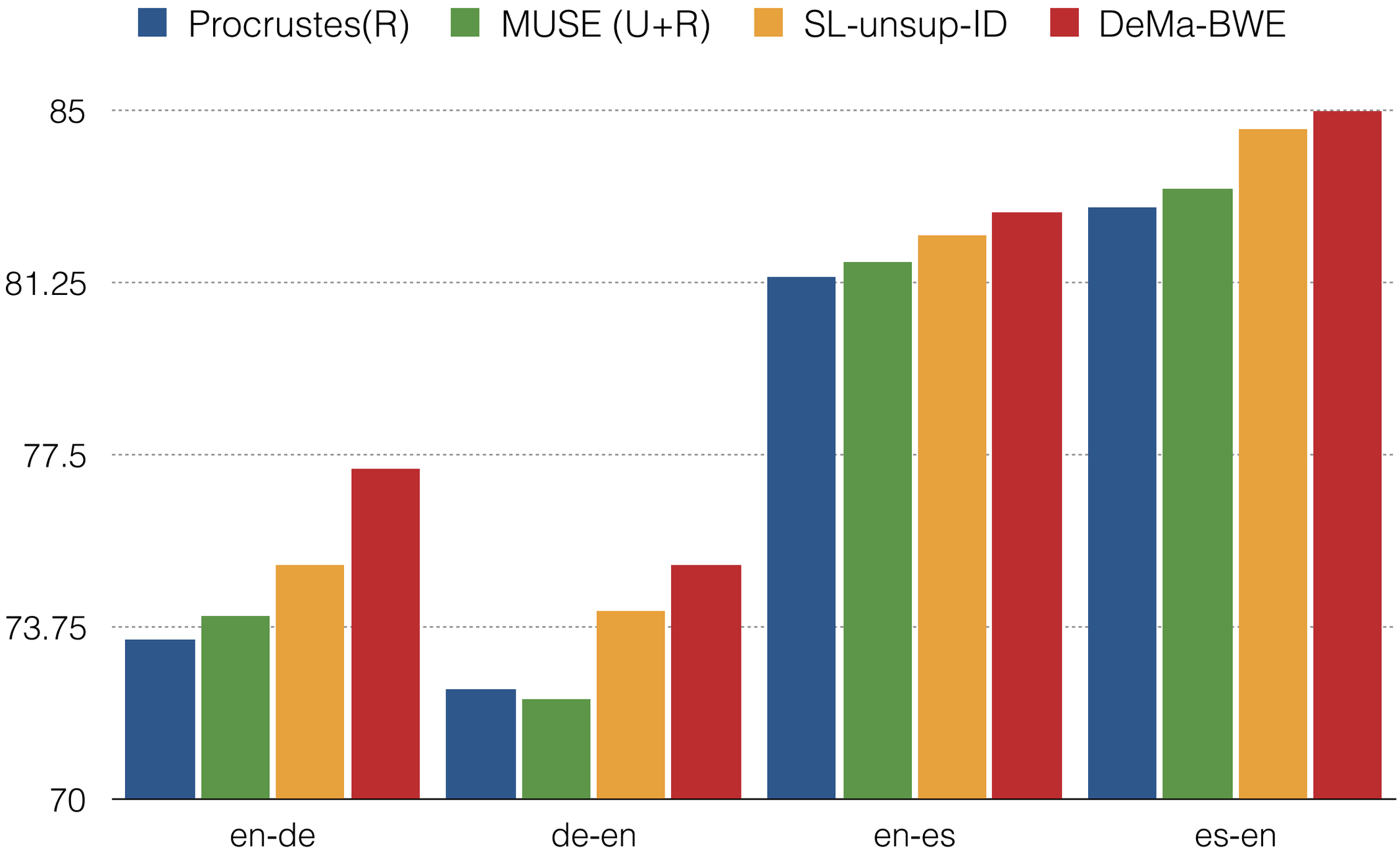
$$\mathrm{CSLS}(\mathbf{x}', \mathbf{y}) = 2\cos(\mathbf{x}', \mathbf{y}) - r_T(\mathbf{x}') - r_S(\mathbf{y})$$

# Experiments

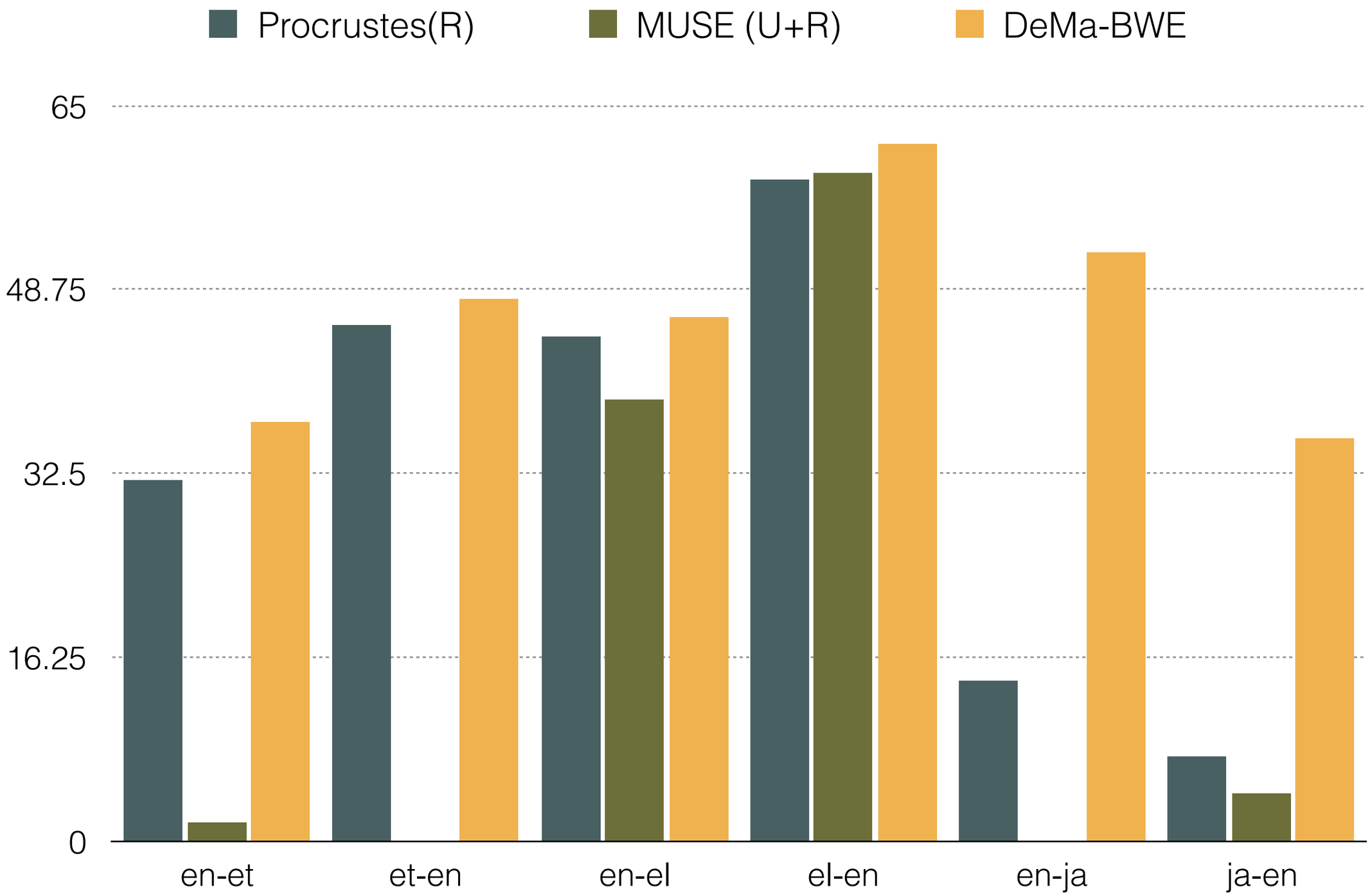
- **Dataset and Tasks**
  - Bilingual Lexicon Induction Task: MUSE dataset (Conneau el al., 2017)
  - Cross-lingual Word Similarity Task: SemEval 2017

- **Languages**
  - Baseline languages: en - es, de, fr, ru, zh, ja
  - Morphologically rich languages: en - et, fi, el, hu, pl, tr

# Main Results on BLI (close languages)



# Main Results on BLI (distant languages)

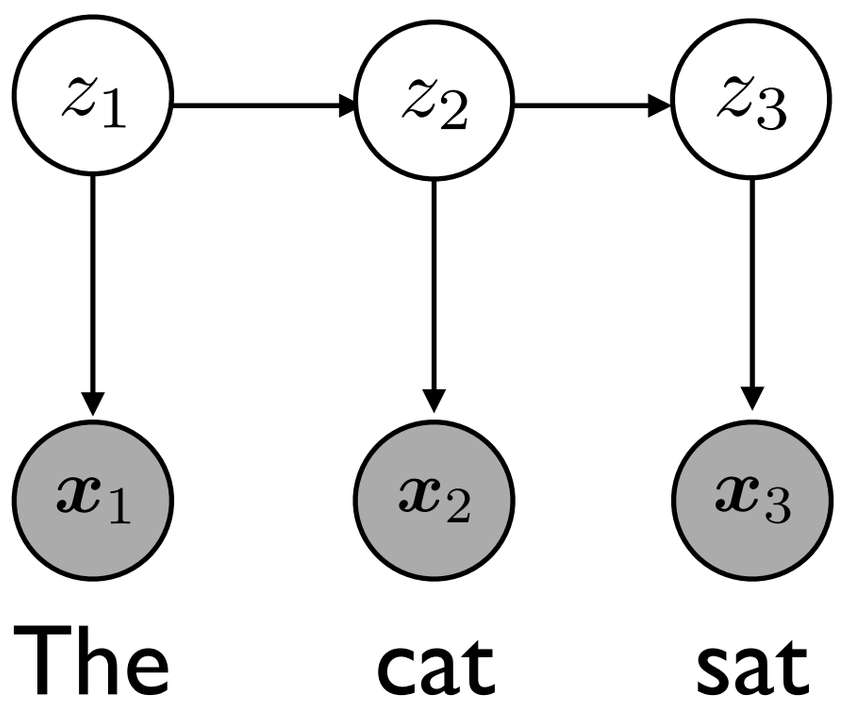


# Unsupervised Learning of Syntactic Structure w/ Invertible Neural Projections

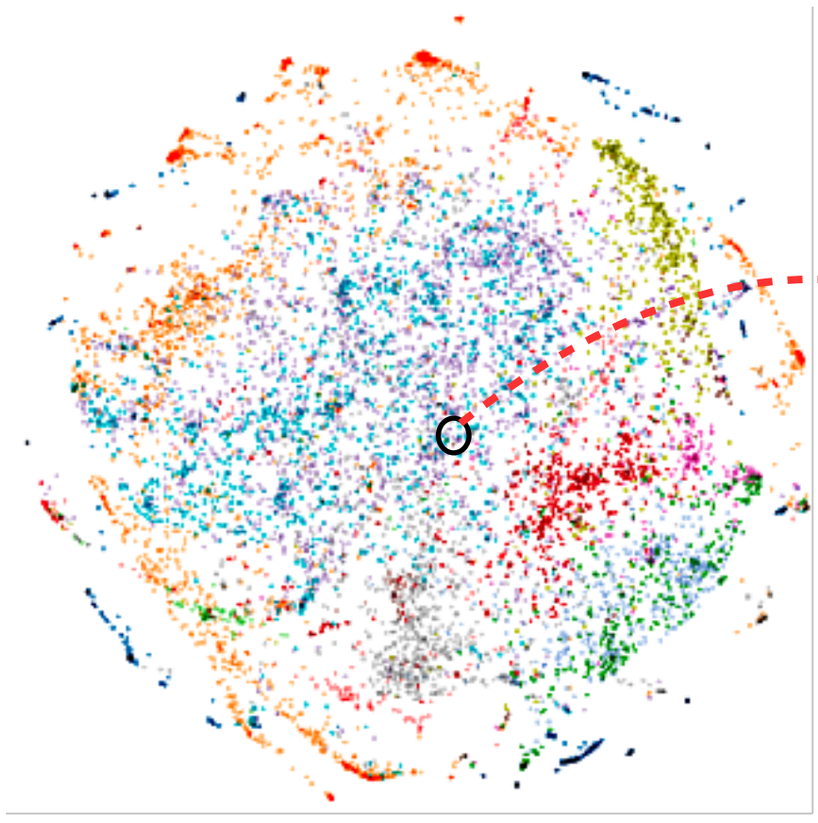
Junxian He, Graham Neubig, Taylor Berg-Kirkpatrick

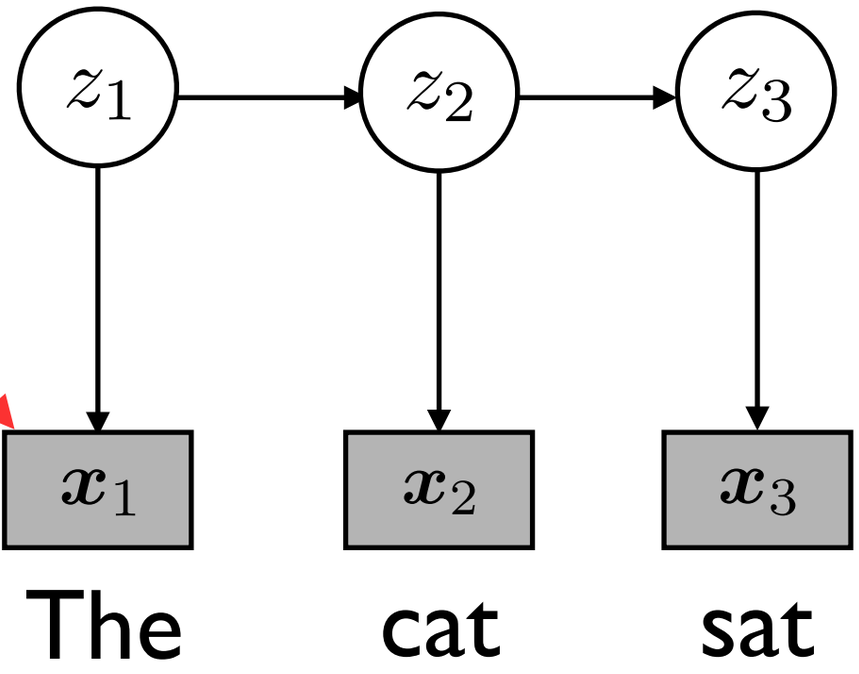
(EMNLP 2018)

# HMM for Part-of-Speech Induction



# Gaussian HMM for POS Induction






$$\boldsymbol{x}_i \sim \mathcal{N}(\boldsymbol{\mu}_{z_i}, \Sigma_{z_i})$$

[Lin et al. 2015]

# Latent Embeddings w/ Neural Projection

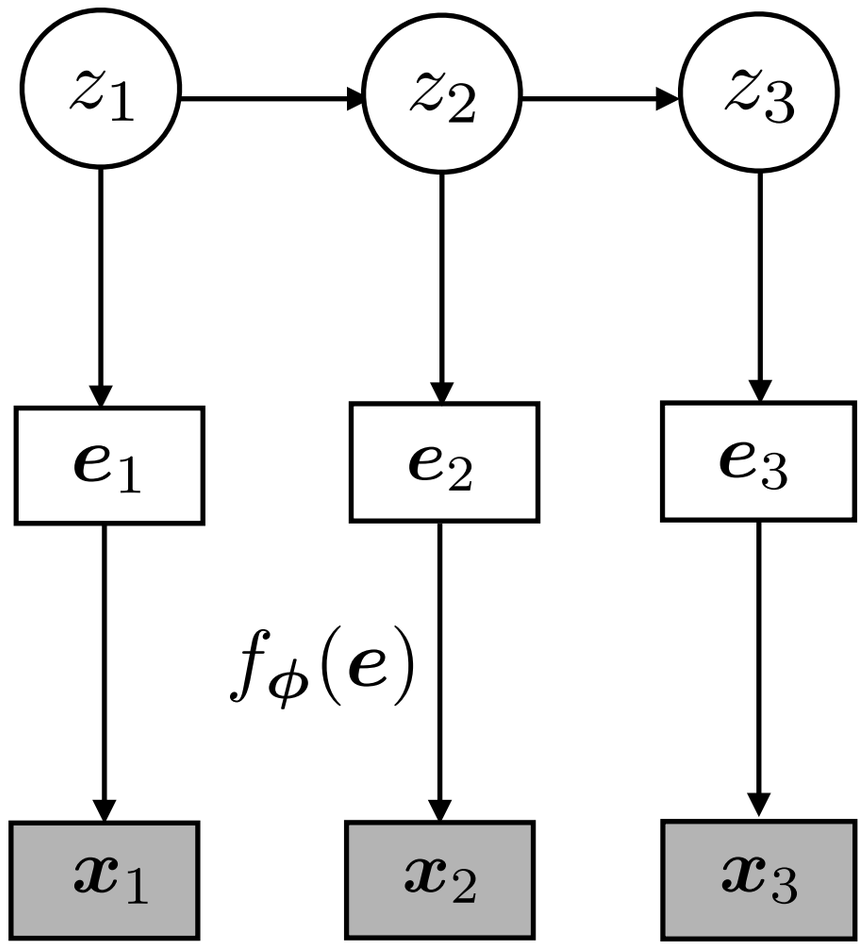
$z_i \sim$ Markov Structure

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

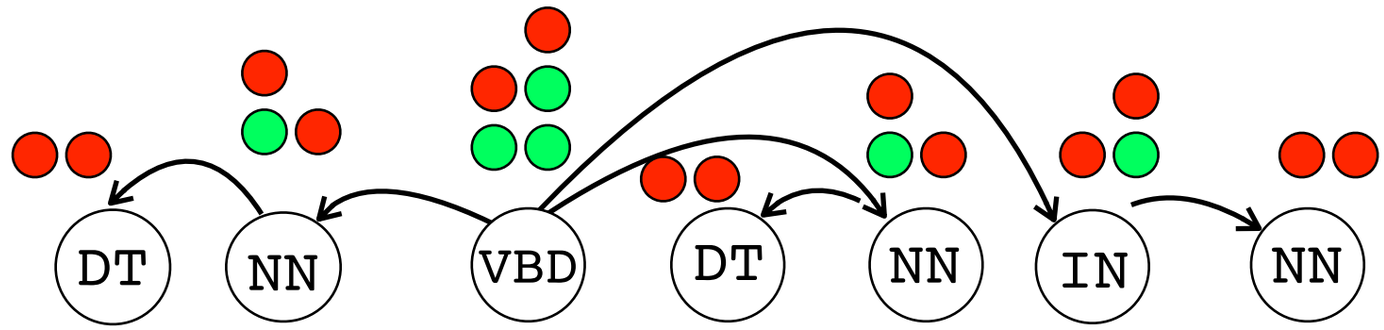

Neural Projector

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

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



# Dependency Model with Valence




[Klein and Manning 2004]

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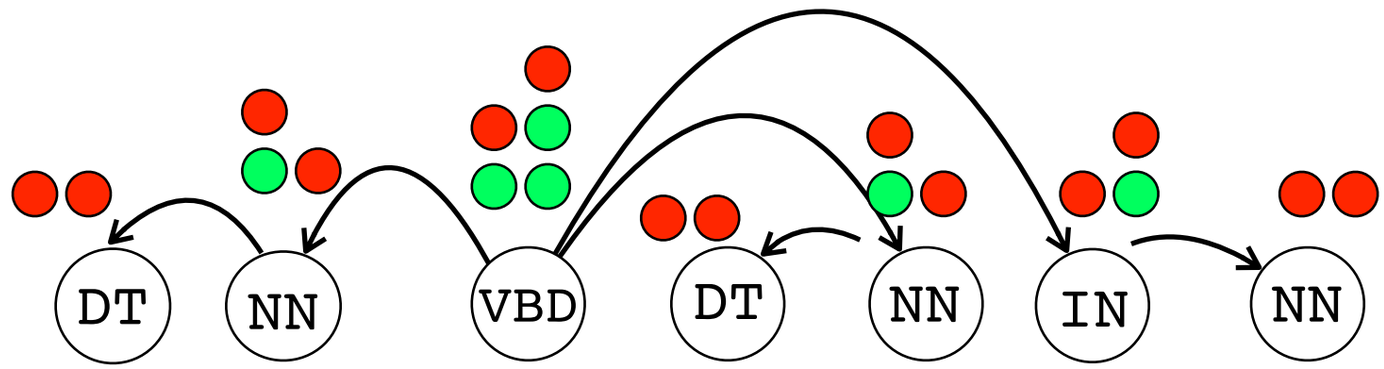
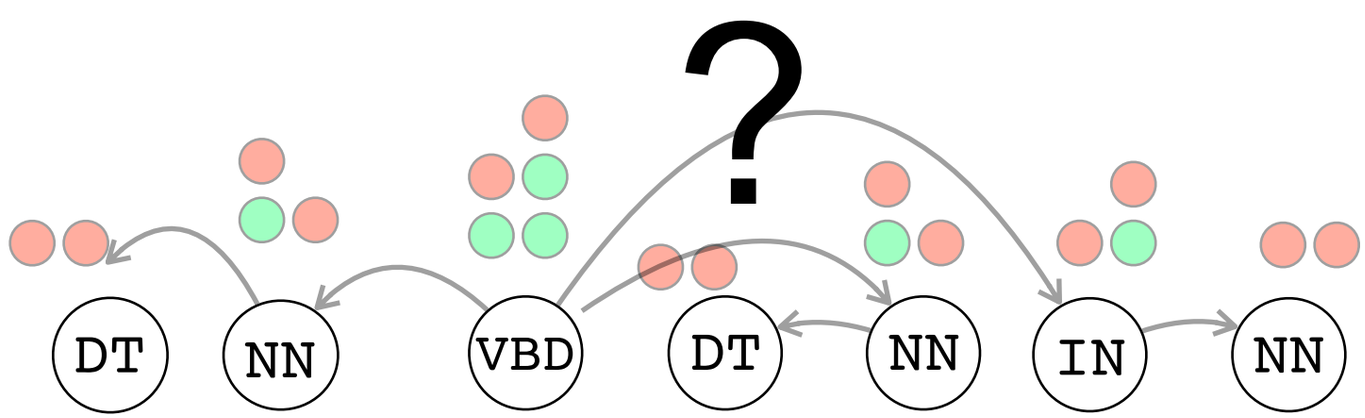
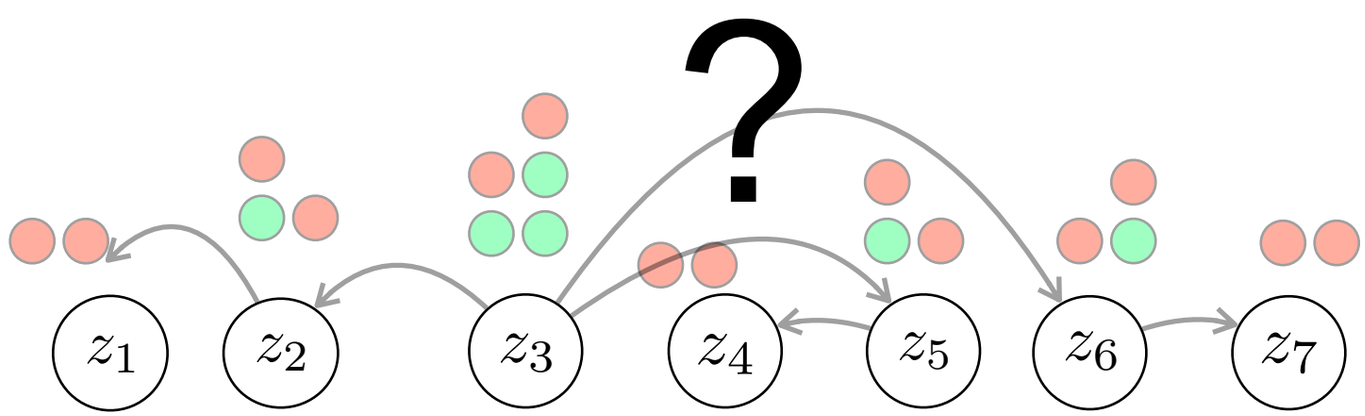



[Klein and Manning 2004]

# Dependency Parse Induction from POS



# Grammar Induction from Raw Text



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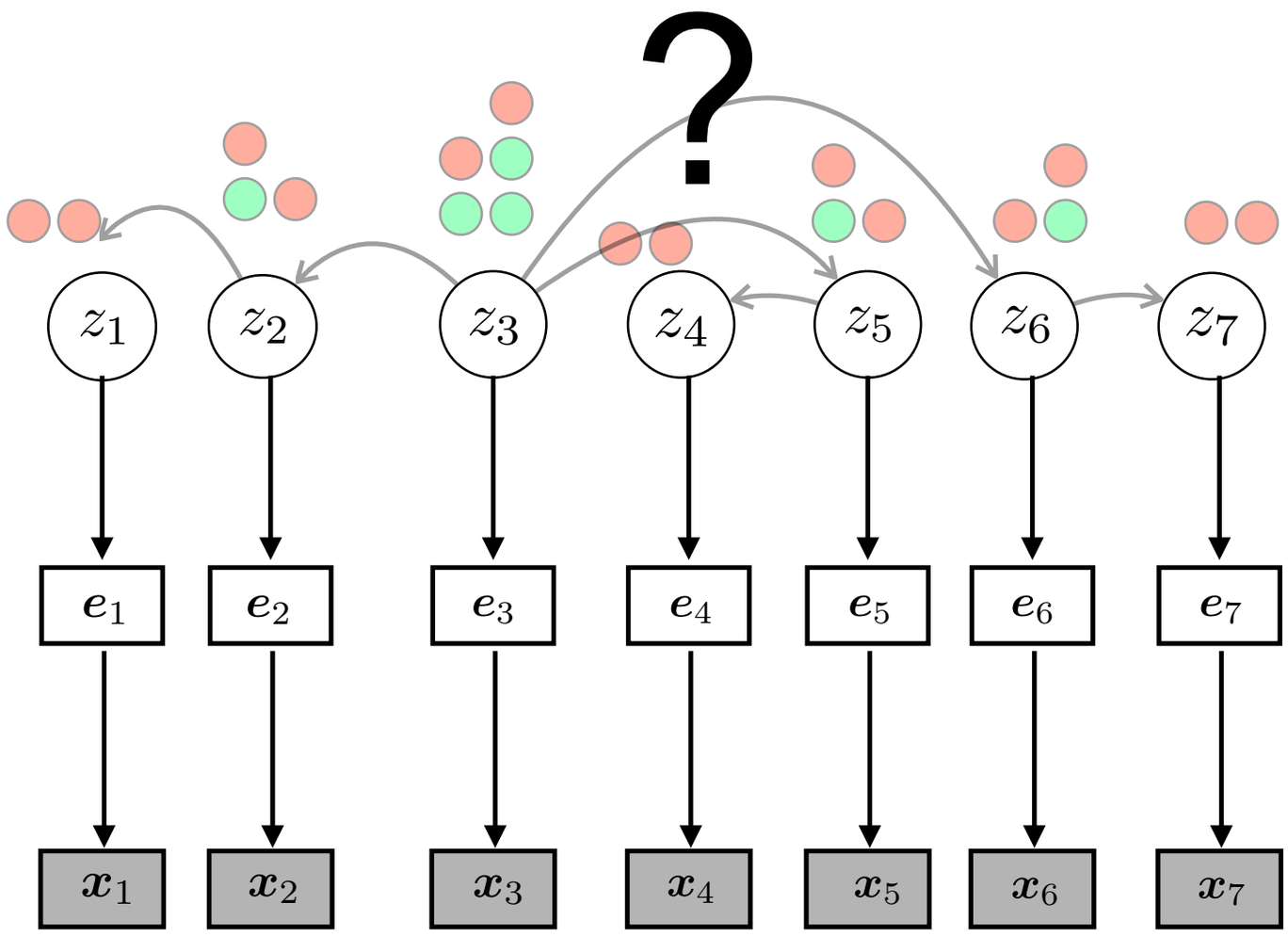
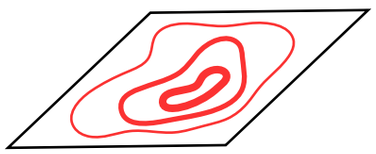


# Latent Embeddings w/ Neural Projection

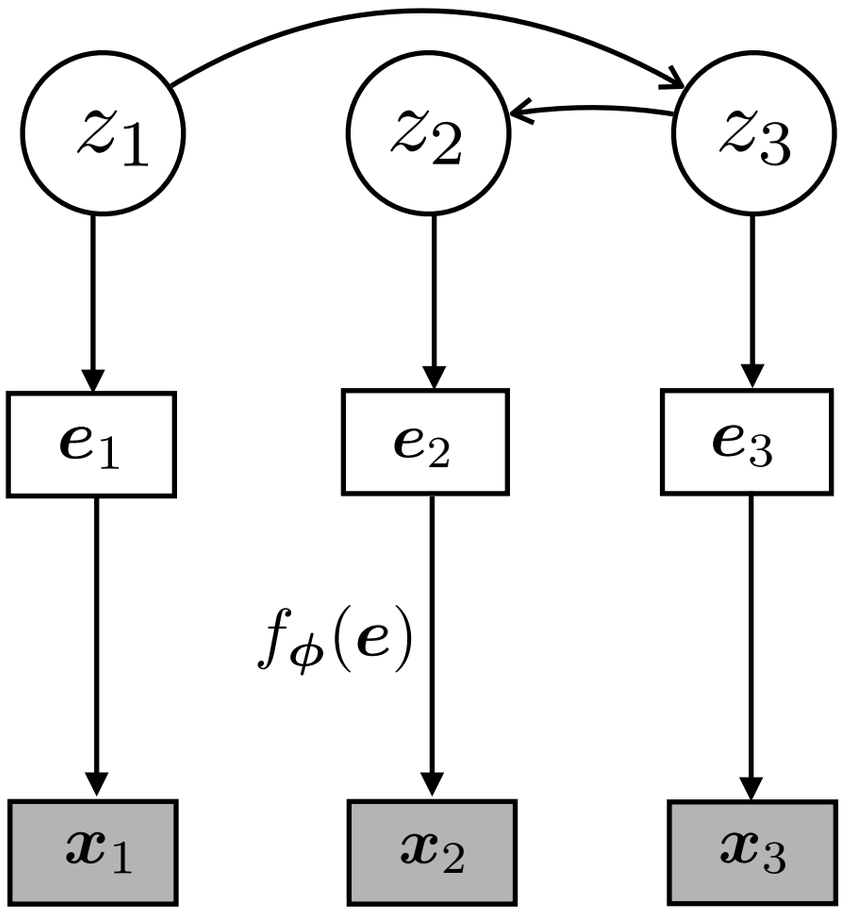
$z_i \sim$ Syntax Model

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

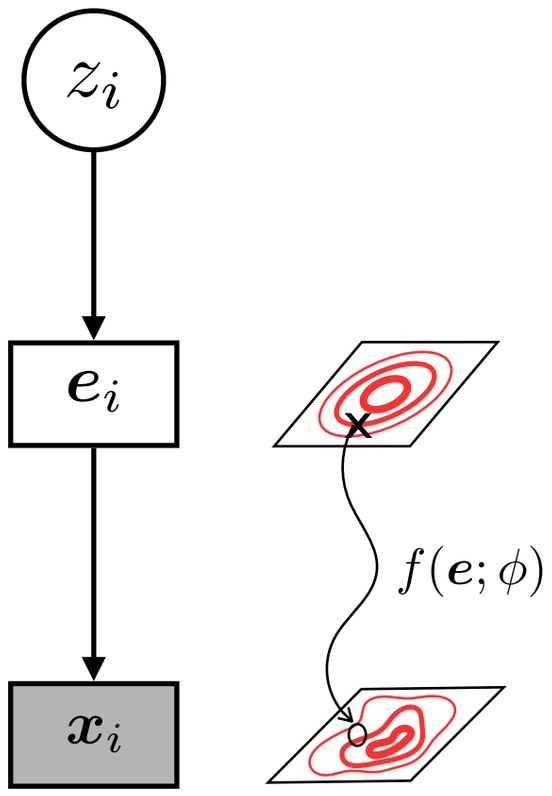
Neural Projector $\boldsymbol{x}_i = f_{\boldsymbol{\phi}}(\boldsymbol{e}_i)$



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

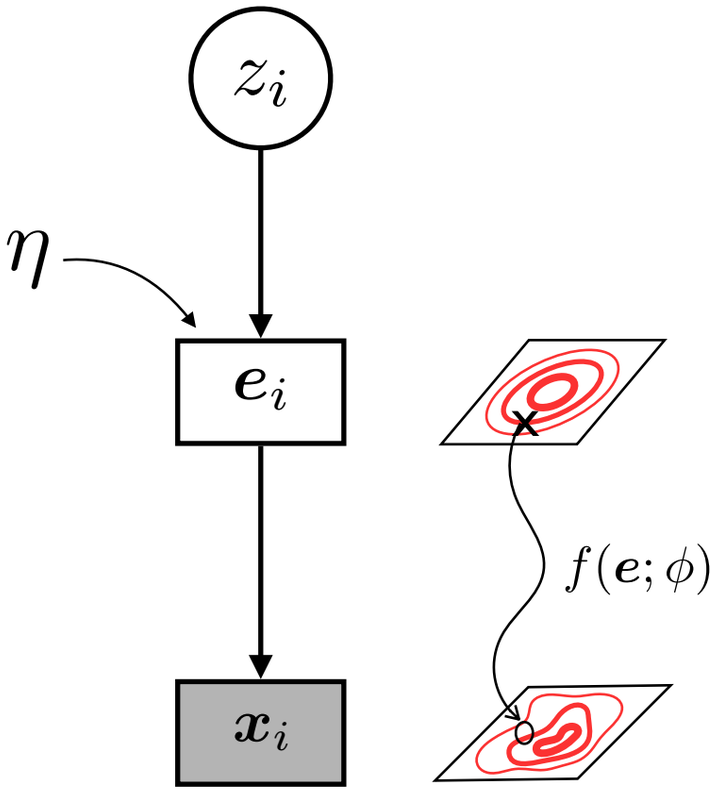


# Learning and Inference




$$p(\boldsymbol{x}_i|z_i;\eta,\phi)$$

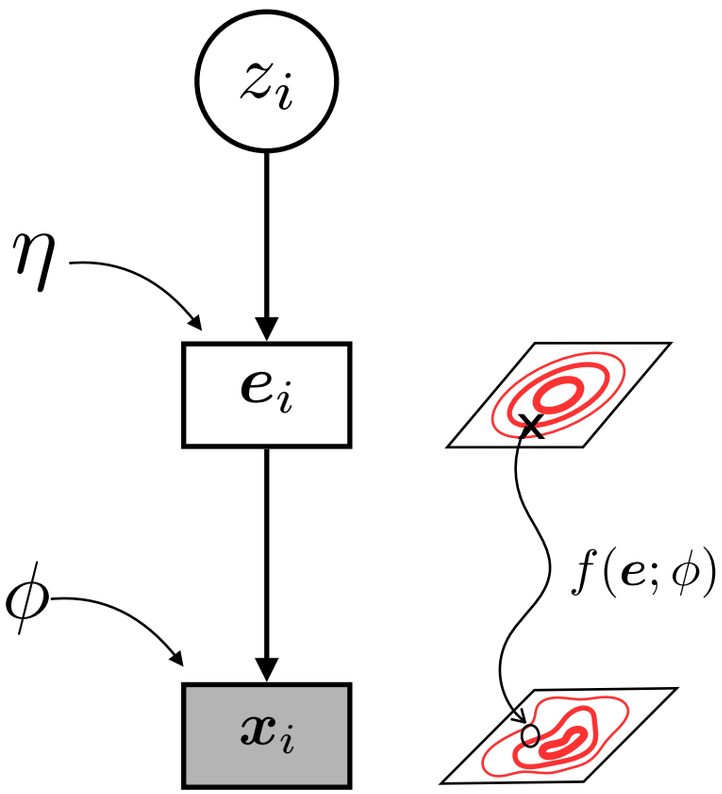
# Learning and Inference




$$p(\boldsymbol{x}_i|z_i;\eta,\phi)$$

Gaussian embedding parameters

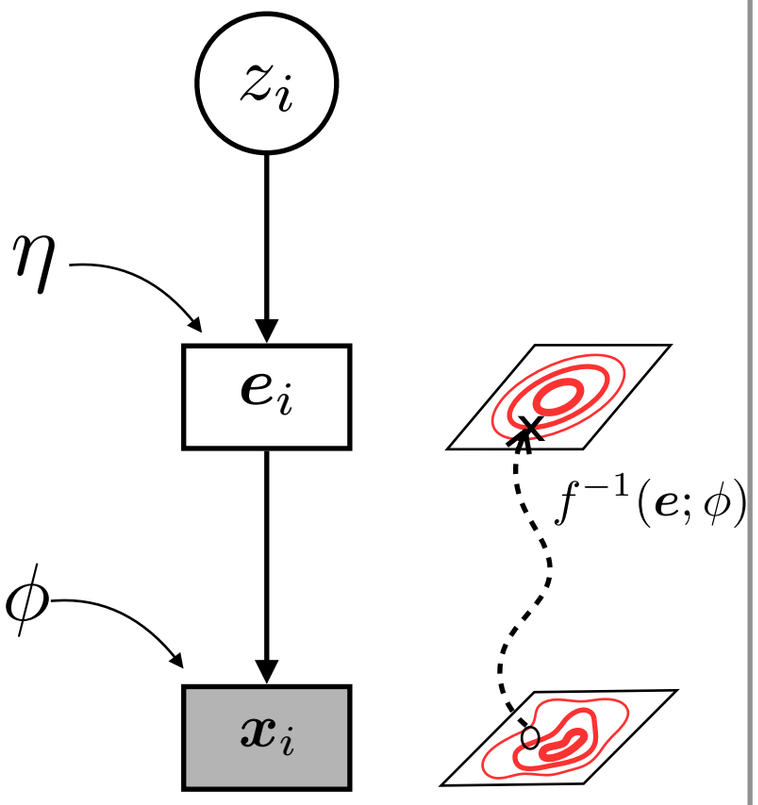
# Learning and Inference




$p(\boldsymbol{x}_i|z_i;\eta,\phi)$

Projection parameters

# Learning and Inference

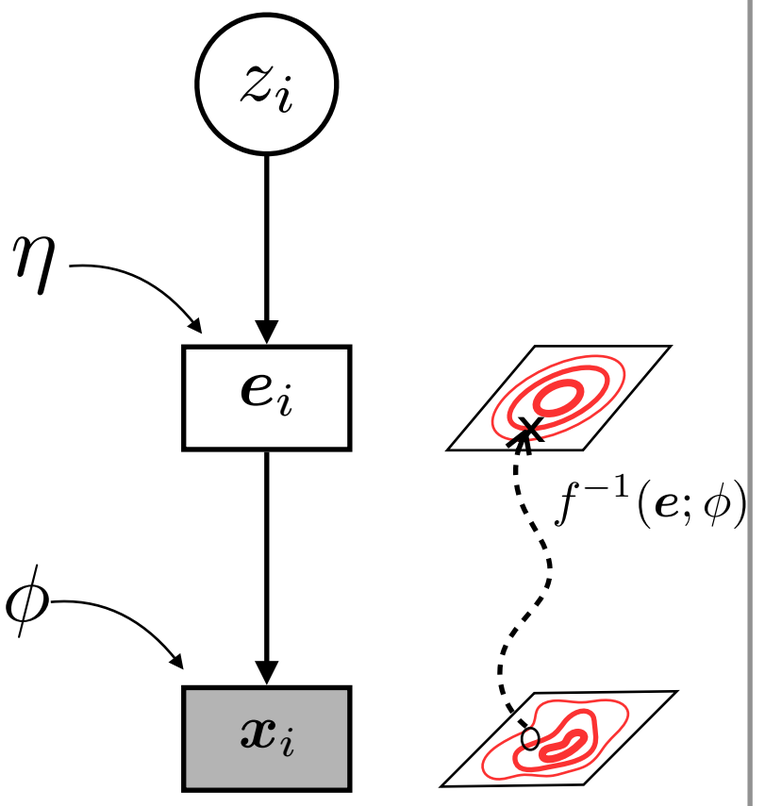



dim(x) = dim(e) and $f$ is invertible

$$p(\boldsymbol{x}_i|z_i;\eta,\phi)$$

$$= p(f_\phi^{-1}(\boldsymbol{x}_i)|z_i;\eta)\left|\det\frac{\partial f^{-1}}{\partial \boldsymbol{x}_i}\right|$$

# Learning and Inference

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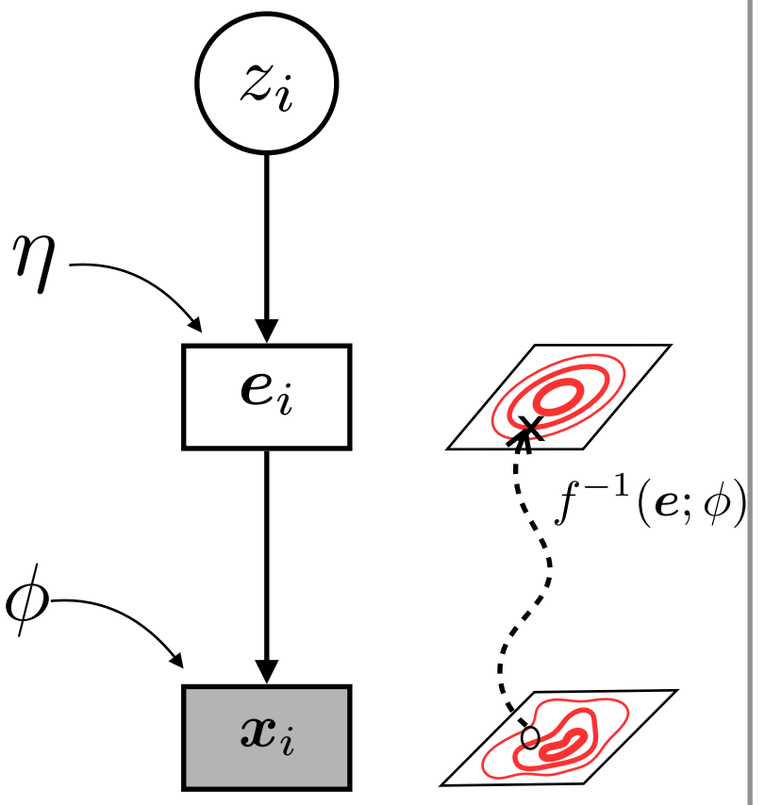
$$= p(f_\phi^{-1}(\boldsymbol{x}_i)|z_i;\eta)\left|\det\frac{\partial f^{-1}}{\partial \boldsymbol{x}_i}\right|$$

Determinant of Jacobian matrix

# Learning and Inference




dim(x) = dim(e) and $f$ is invertible

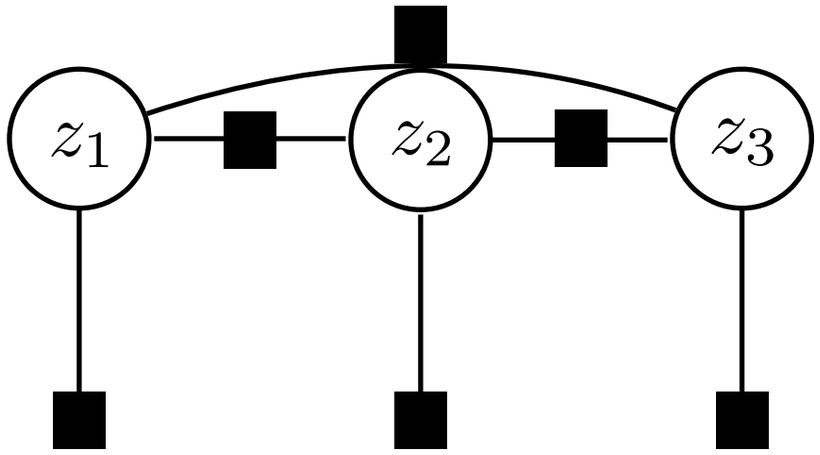
$$p(\boldsymbol{x}_i|z_i;\eta,\phi)$$

$$= p(f_\phi^{-1}(\boldsymbol{x}_i)|z_i;\eta)\left|\det\frac{\partial f^{-1}}{\partial \boldsymbol{x}_i}\right|$$

Gaussian distribution

Determinant of Jacobian matrix

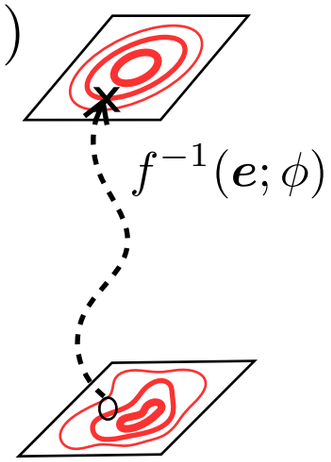
# Learning and Inference




$$p(f_\phi^{-1}(\boldsymbol{x}_i)|z_i;\eta)\left|\det\frac{\partial f^{-1}}{\partial \boldsymbol{x}_i}\right|$$

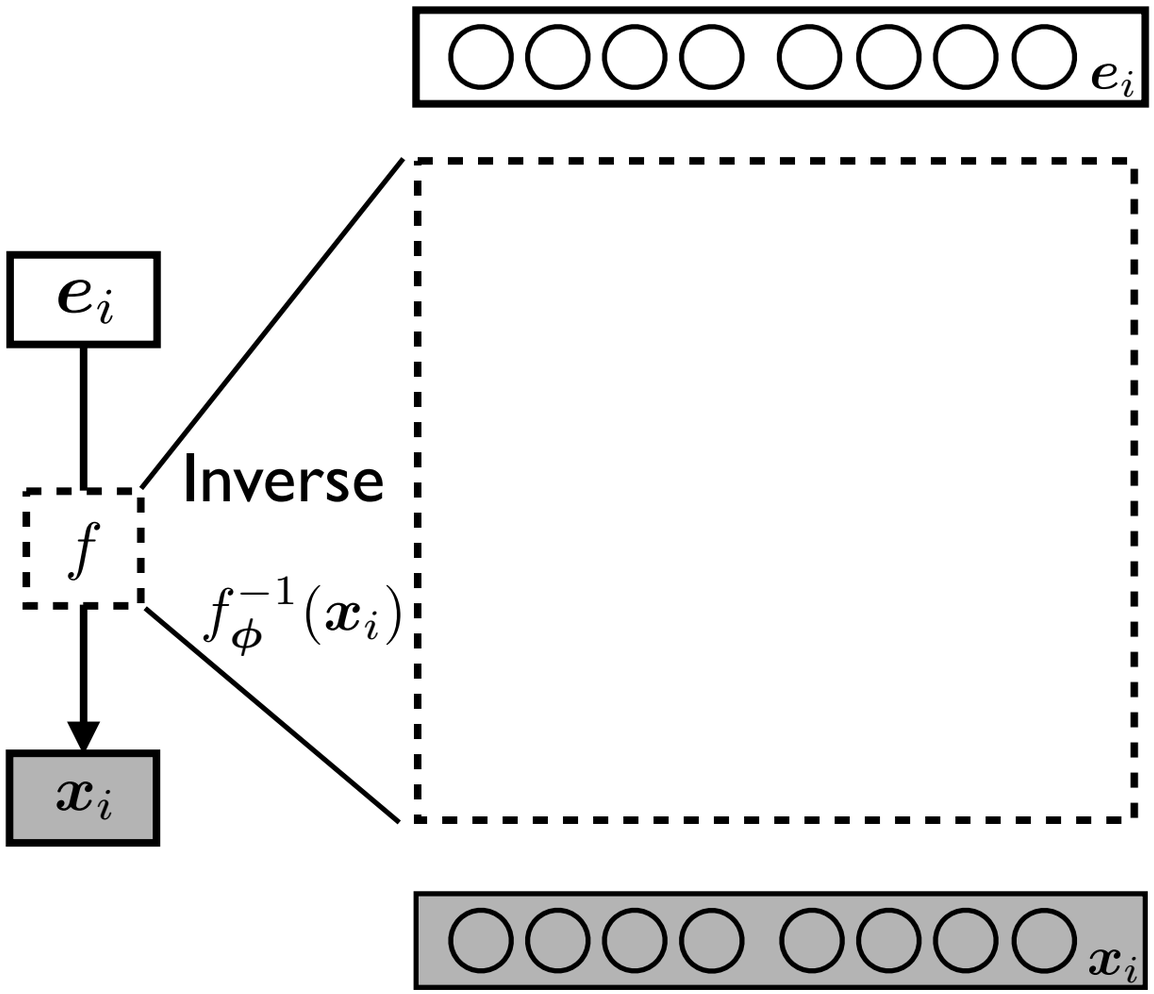
## Example of Markov prior

$$\log p(\boldsymbol{x}) = \log p_{\text{GHMM}}(f_\phi^{-1}(\boldsymbol{x})) + \sum \log\left|\det\frac{\partial f_\phi^{-1}}{\partial \boldsymbol{x}_i}\right|$$

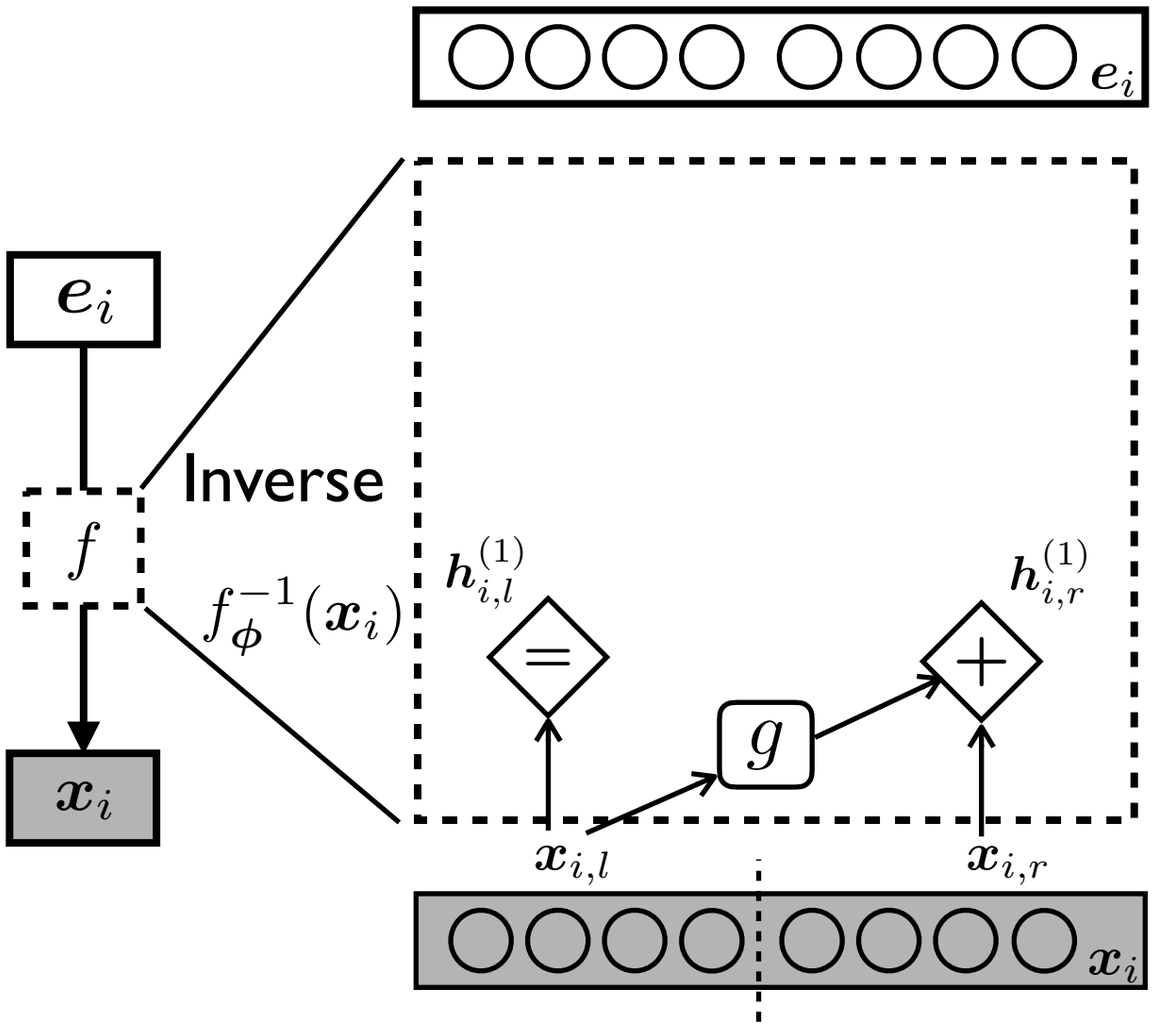



$-\infty$ when $f$ is not invertible

# Learning with Inverse Projection

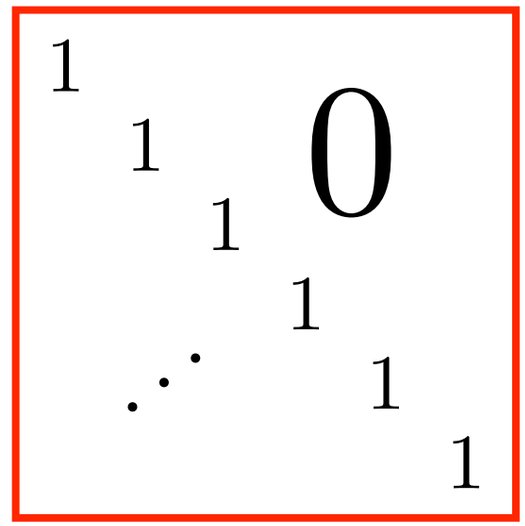


# Learning with Inverse Projection



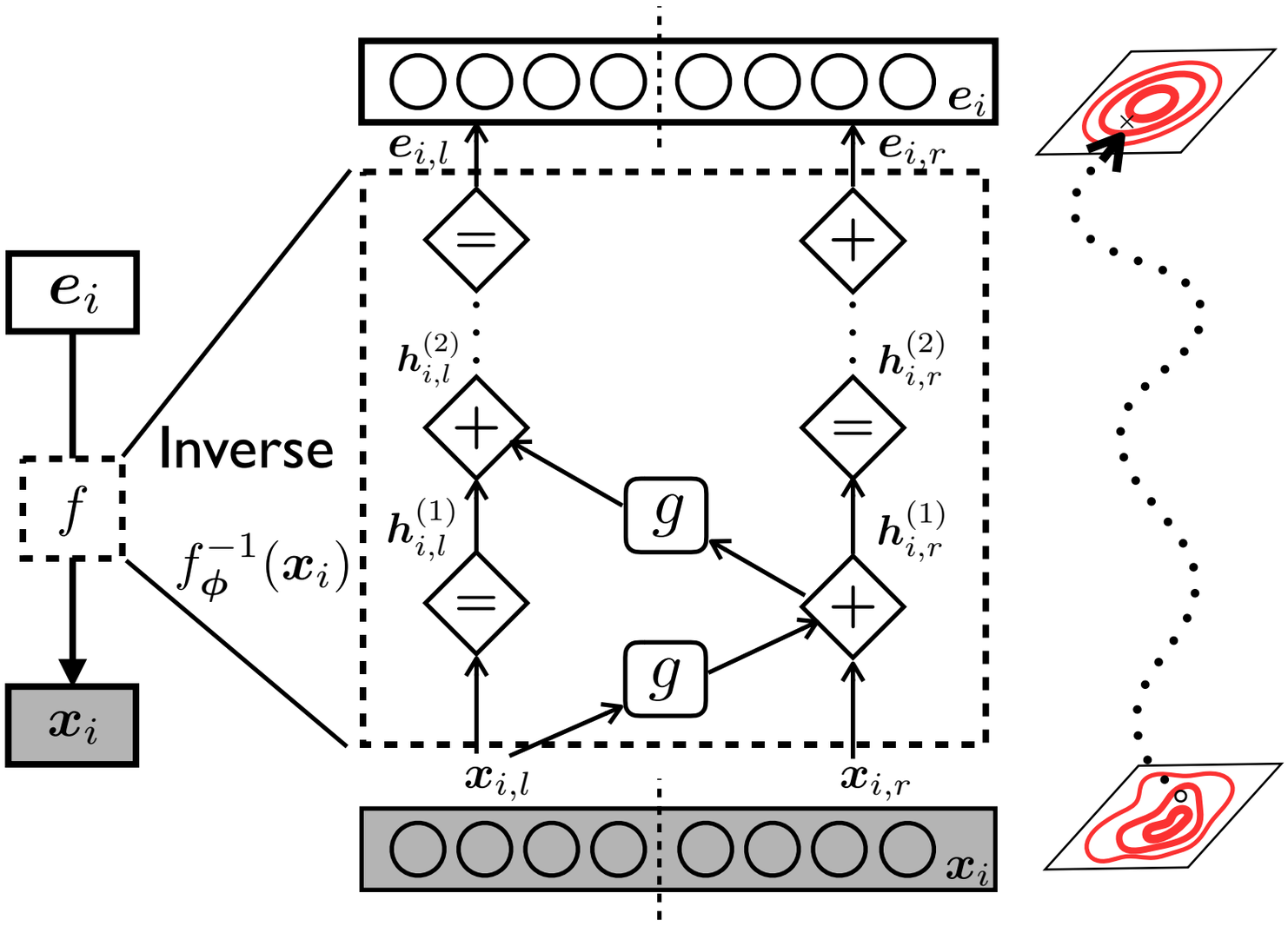

$$h_{i,l}^{(1)} = x_{i,l}$$

$$h_{i,r}^{(1)} = x_{i,r} + g(x_{i,l})$$



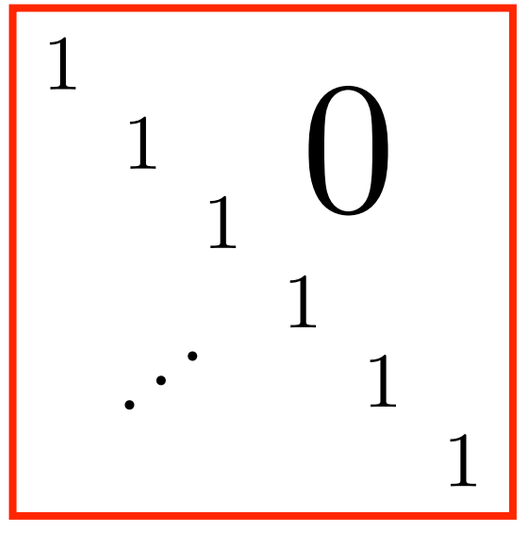

[Dinh et al. 2014]

# Learning with Inverse Projection




$$h_{i,l}^{(1)} = x_{i,l}$$

$$h_{i,r}^{(1)} = x_{i,r} + g(x_{i,l})$$




[Dinh et al. 2014]

# Experiments

- Dataset: English Penn Treebank
- POS tagging

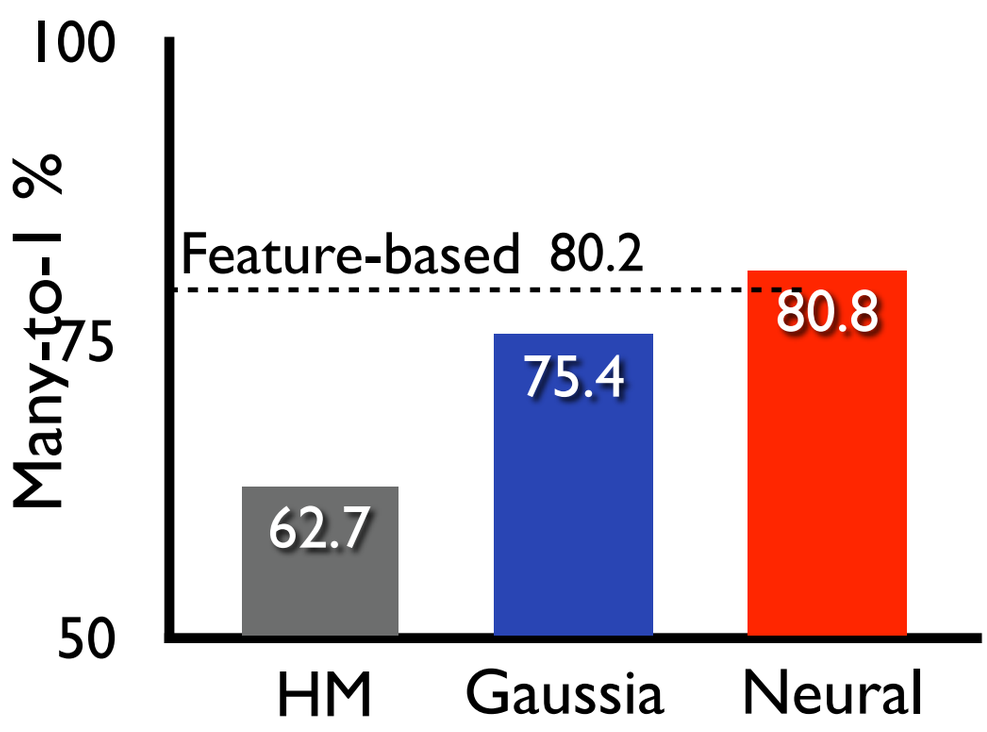
# Trained and tested on whole PTB

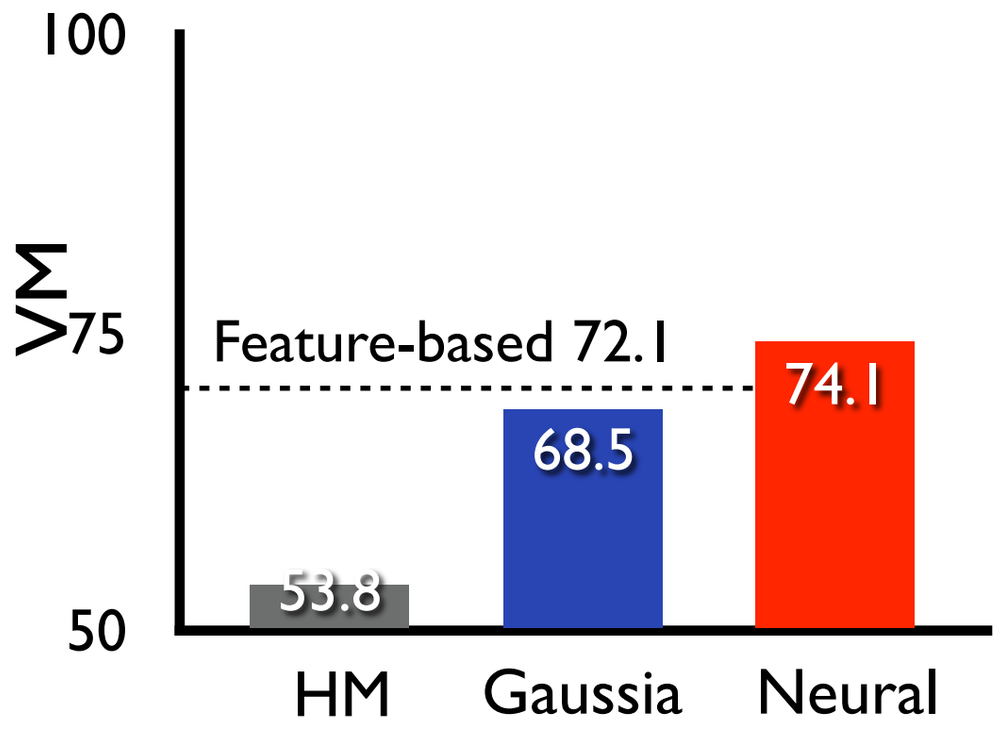
- Grammar induction

Trained on sentences of length <= 10 in section 2-21

Tested on sentences in section 23

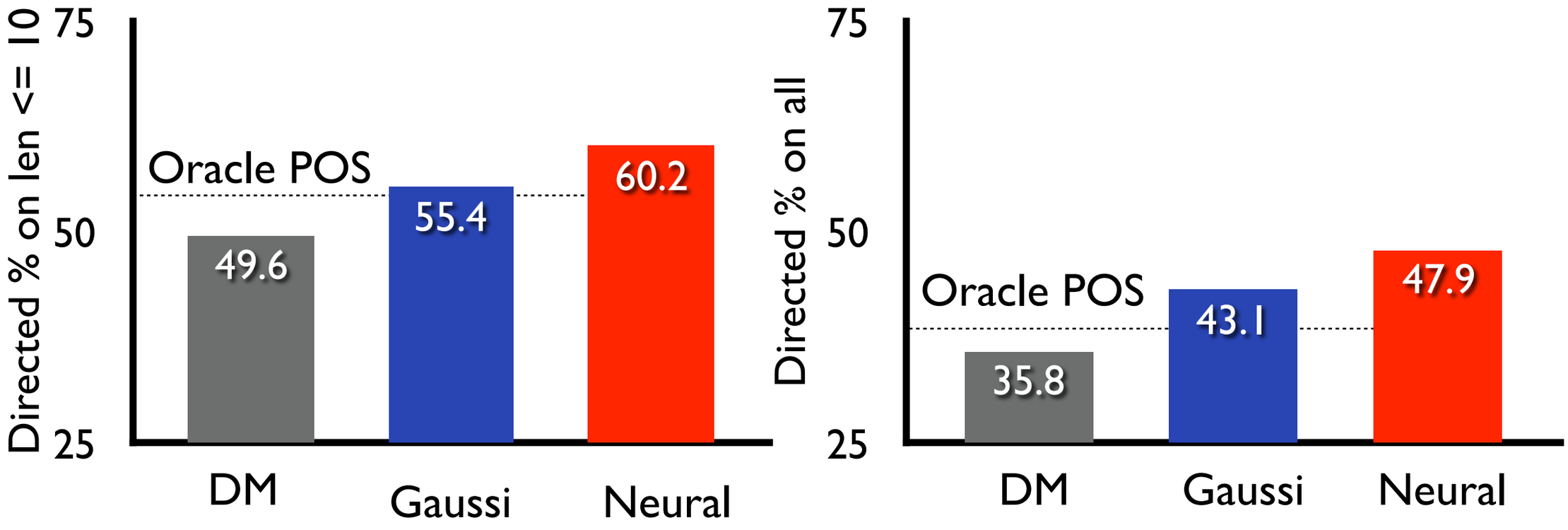
# Part-of-speech Induction



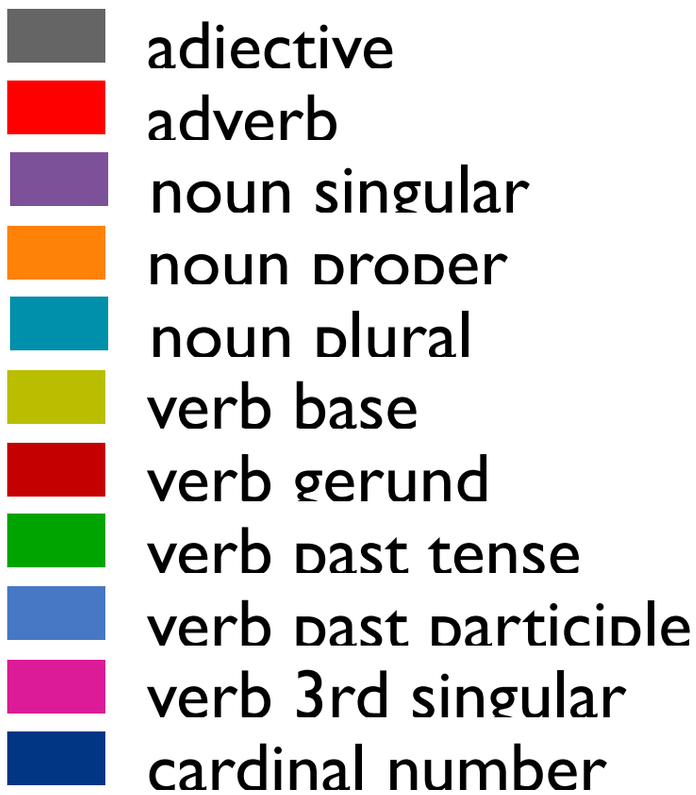




Outperform feature-based SOTA

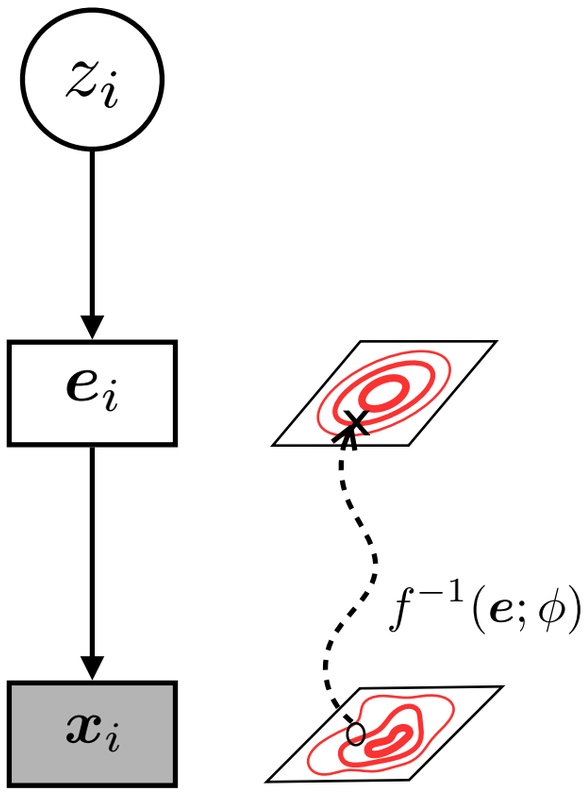
# Dependency Parse Induction

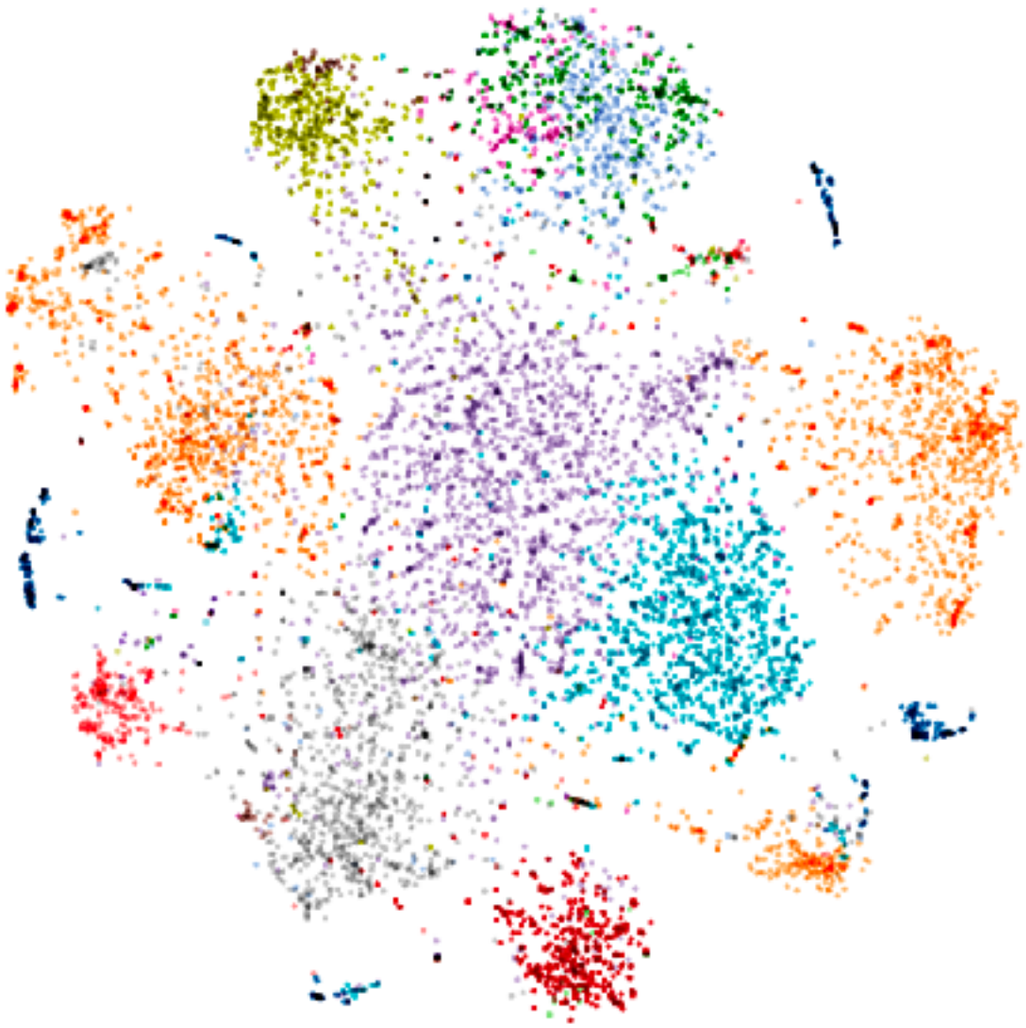


# Original Embedding Space

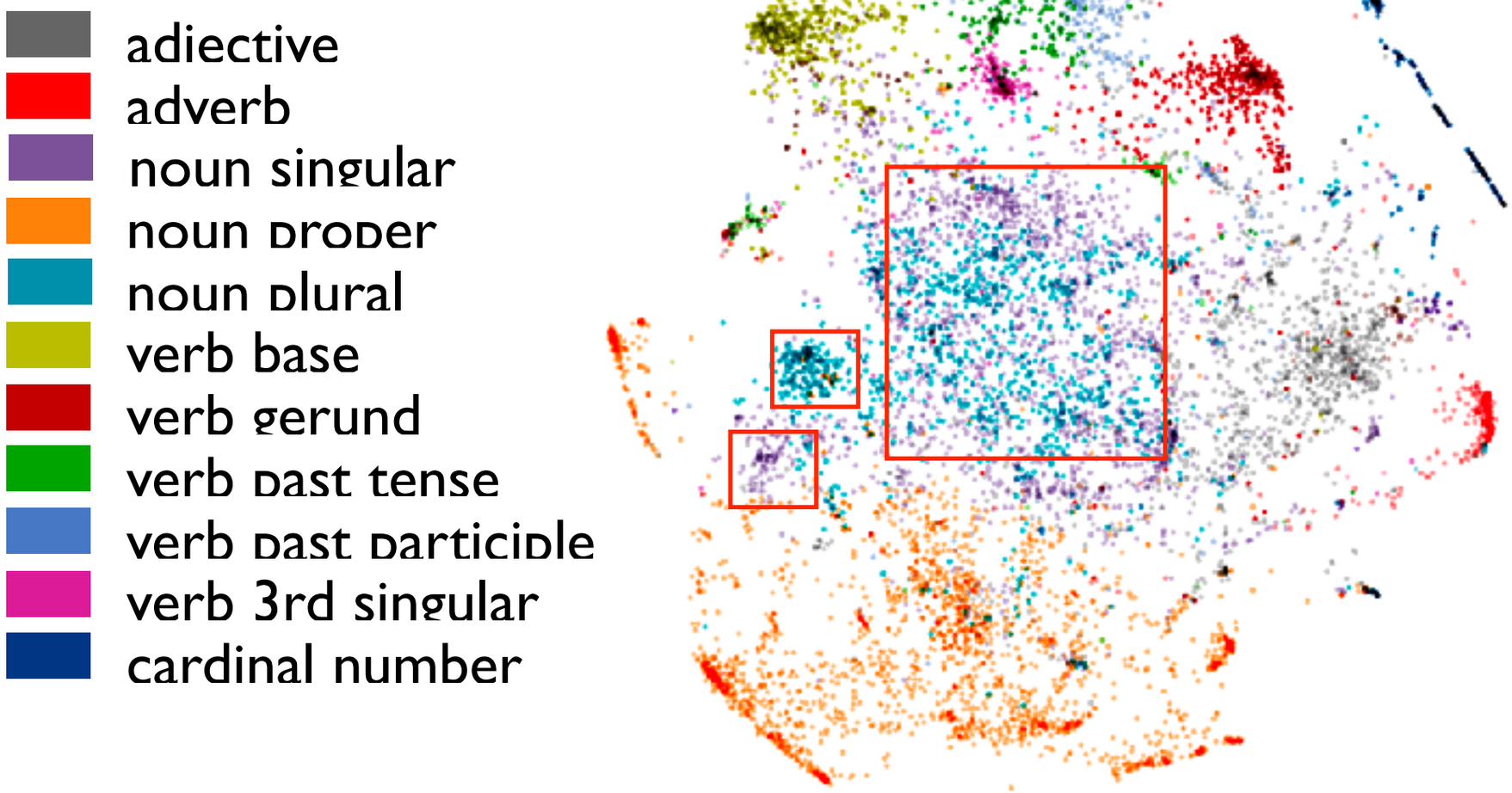



# Projected Embedding Space w/ Markov Prior

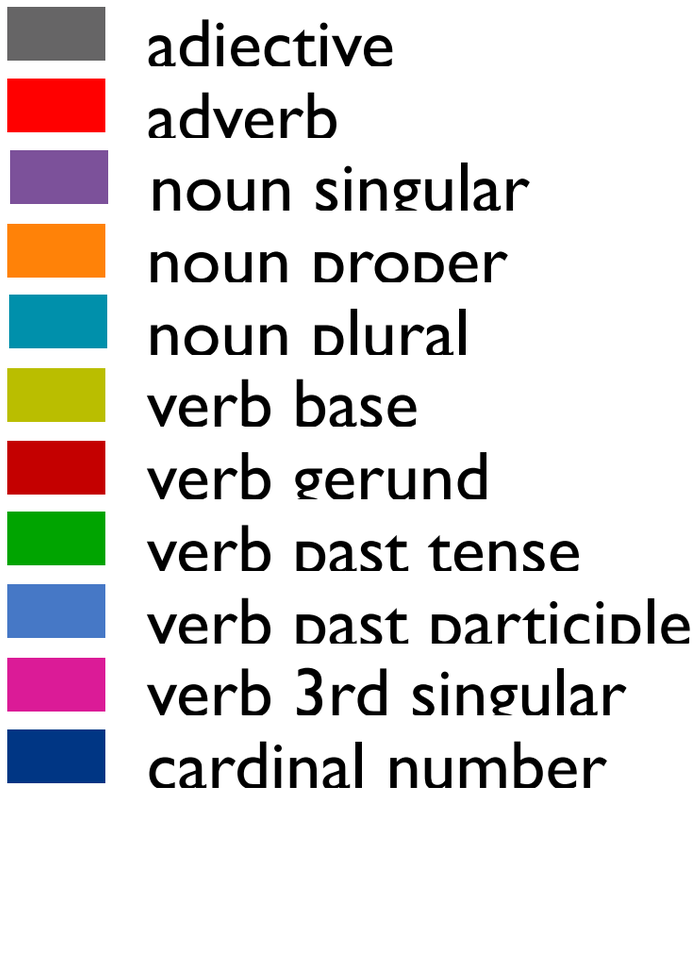


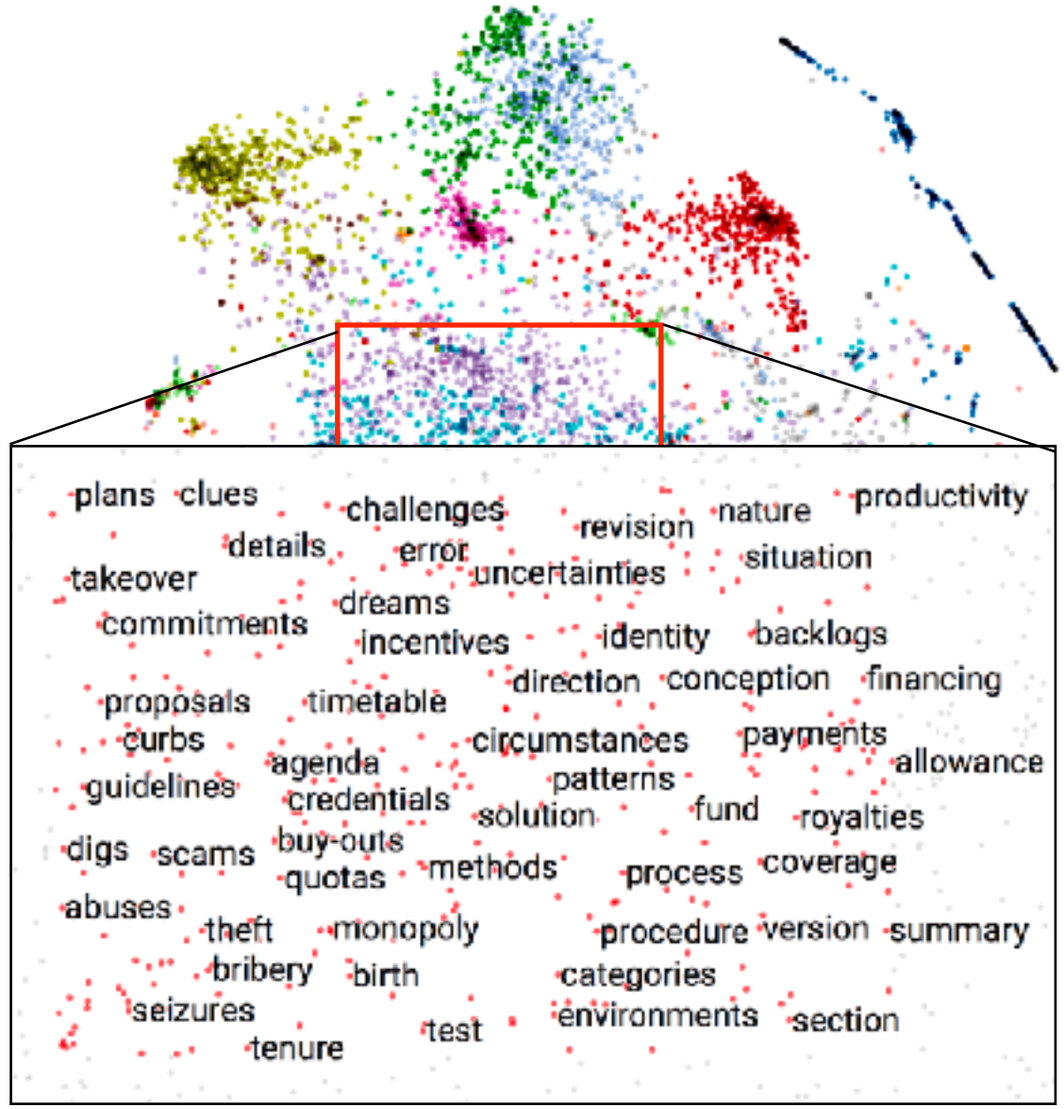



# Projected Embedding Space w/ DMV Prior

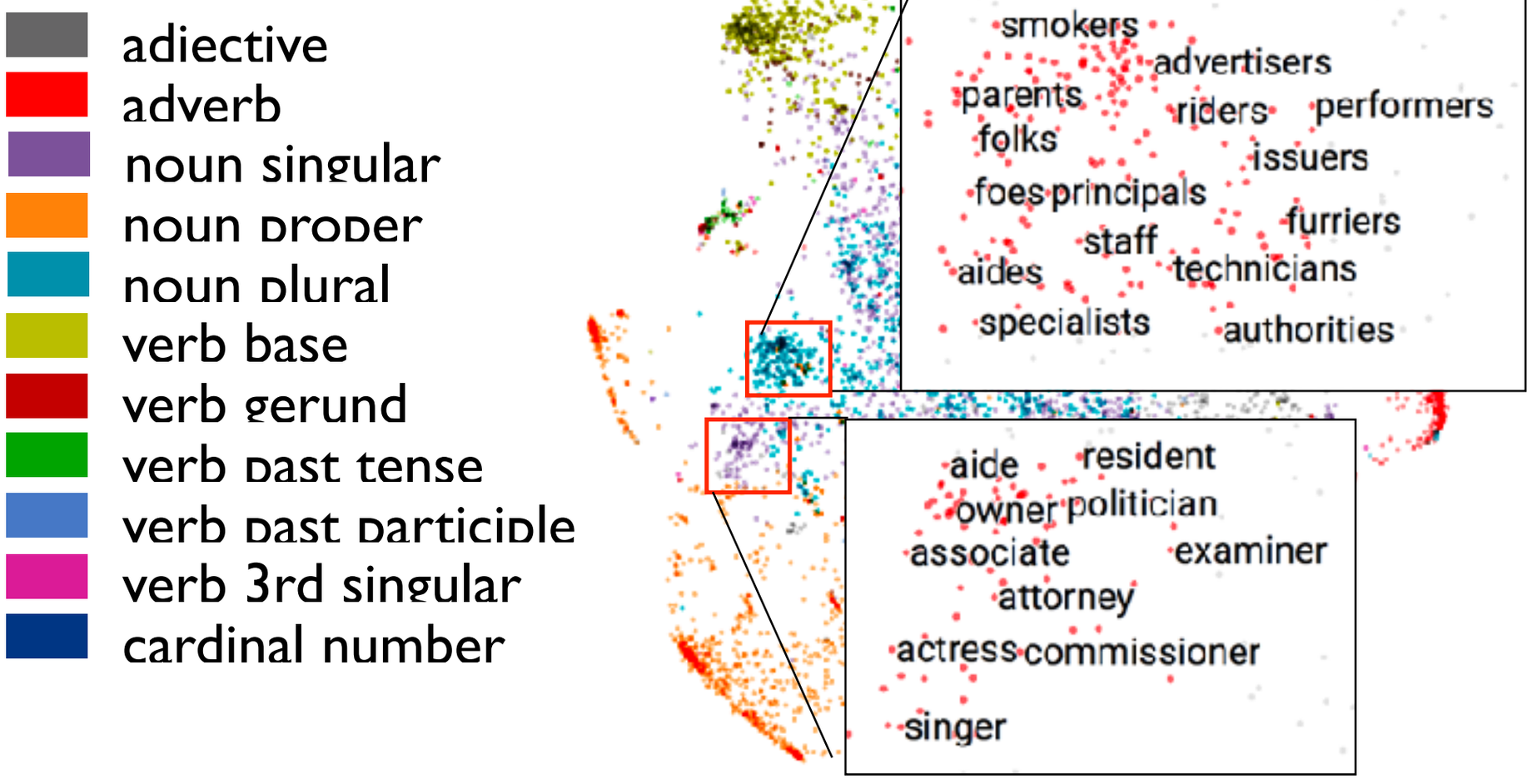


# Projected Embedding Space w/ DMV Prior



# Projected Embedding Space w/ DMV Prior



# FlowSeq: Non-Autoregressive Conditional Sequence Generation with Generative

Xuezhe Ma*, Chunting Zhou*, Xian Li, Graham Neubig, Eduard Hovy

# Background

- Autoregressive Sequence Generation

$$P_\theta(\mathbf{y}|\mathbf{x}) = \prod_{t=1}^{T} P_\theta(y_t|y_{<t}, \mathbf{x}).$$

  - Left-to-right factorization is not optimal
  - Generation is not easily parallelizable on GPUs
- Non-autoregressive Sequence Generation

$$P_\theta(\mathbf{y}|\mathbf{x}) = \prod_{t=1}^{T} P_\theta(y_t|\mathbf{x}).$$

# Motivation

- Latent Variable Model

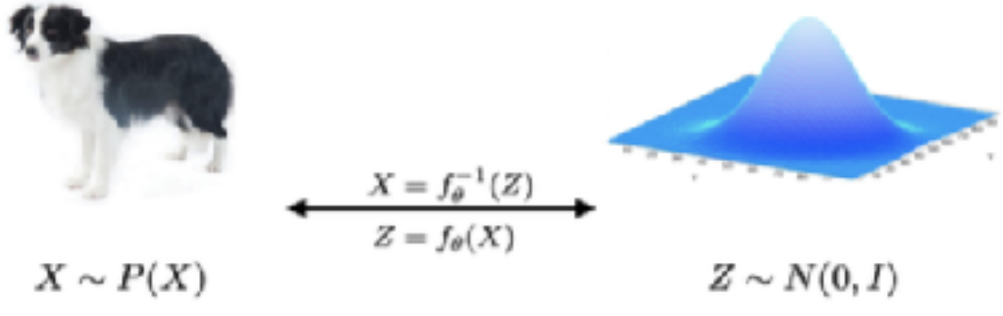
$$P_\theta(\mathbf{y}|\mathbf{x}) = \int_{\mathbf{z}} P_\theta(\mathbf{y}|\mathbf{z},\mathbf{x}) p_\theta(\mathbf{z}|\mathbf{x}) d\mathbf{z},$$

  - $p_\theta(\mathbf{z}|\mathbf{x})$ is the prior distribution over latent z
  - $P_\theta(\mathbf{y}|\mathbf{z},\mathbf{x})$ is the generative distribution (a.k.a decoder)
  - non-autoregressive generation

$$P_\theta(\mathbf{y}|\mathbf{z},\mathbf{x}) = \prod_{t=1}^{T} P_\theta(y_t|\mathbf{z},\mathbf{x}).$$

# Reminder: Flow-based Generative Models

- What is Generative Flows:
  - Transform a simple distribution into a complex one through a chain of invertible transformations



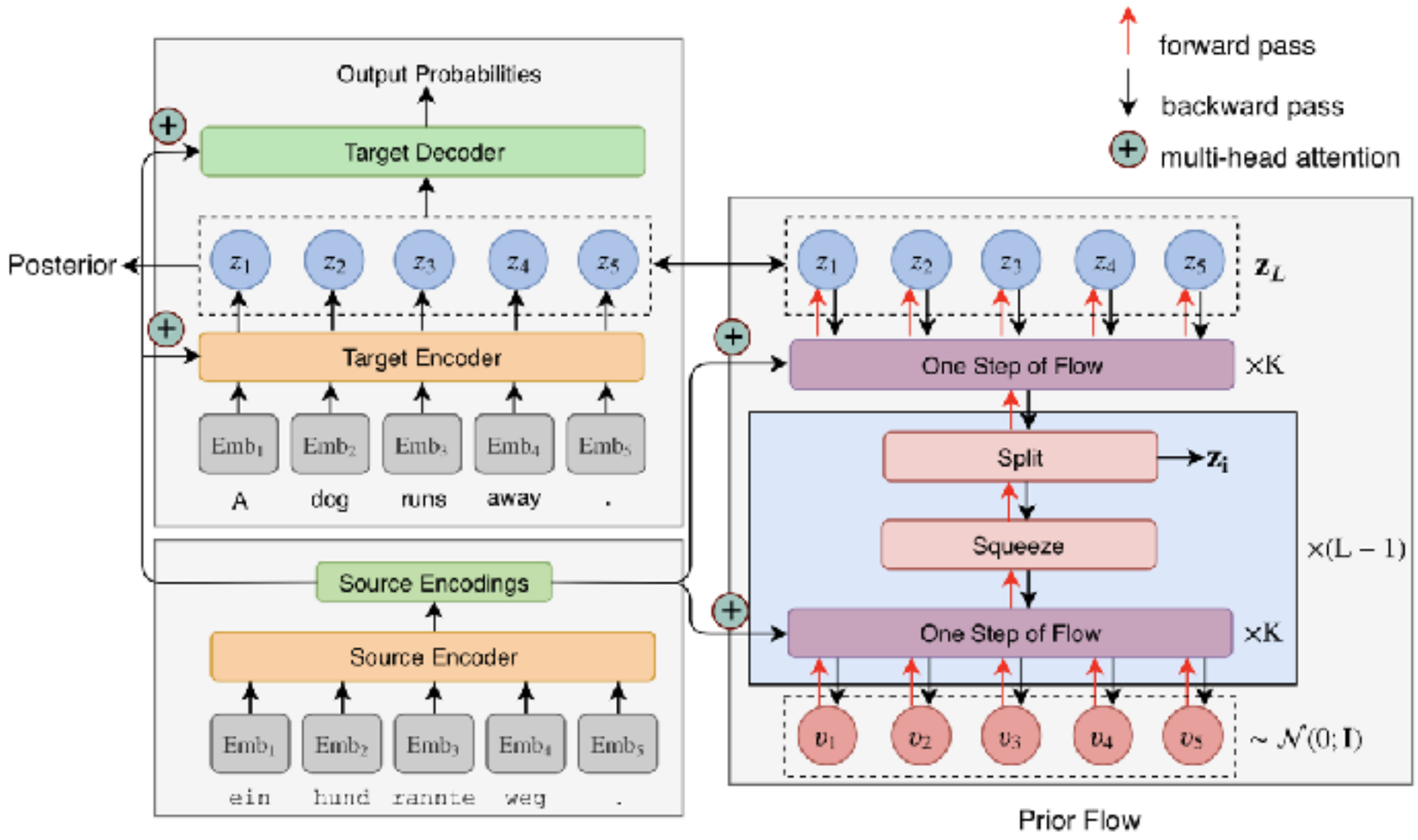

  - Change of variable formula: $$p_\theta(\mathbf{z}) = p_\Upsilon(f_\theta(\mathbf{z}))\left|\det(\frac{\partial f_\theta(\mathbf{z})}{\partial \mathbf{z}})\right|.$$

  - Generative Flow: $$\mathbf{z} \underset{g_1}{\overset{f_1}{\longleftrightarrow}} H_1 \underset{g_2}{\overset{f_2}{\longleftrightarrow}} H2 \underset{g_3}{\overset{f_3}{\longleftrightarrow}} \cdots \underset{g_K}{\overset{f_K}{\longleftrightarrow}} \boldsymbol{v},$$

# FlowSeq

- Variational Training: FlowSeq optimizes the *evidence lower bound* (ELBO)

$$\log P_\theta(\mathbf{y}|\mathbf{x}) \geq \mathrm{E}_{q_\phi(\mathbf{z}|\mathbf{y},\mathbf{x})}[\log P_\theta(\mathbf{y}|\mathbf{z},\mathbf{x})] - \mathrm{KL}(q_\phi(\mathbf{z}|\mathbf{y},\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})).$$



# FlowSeq Architecture

- Source Encoder
  - Standard Transformer encoder
- Posterior: diagonal Gaussian
  - The latent variables z are represented as a sequence of continuous random variables with the same length as the target sequence y:
  -

$$\mathbf{z} = \{\mathbf{z}_1, \ldots, \mathbf{z}_T\}$$

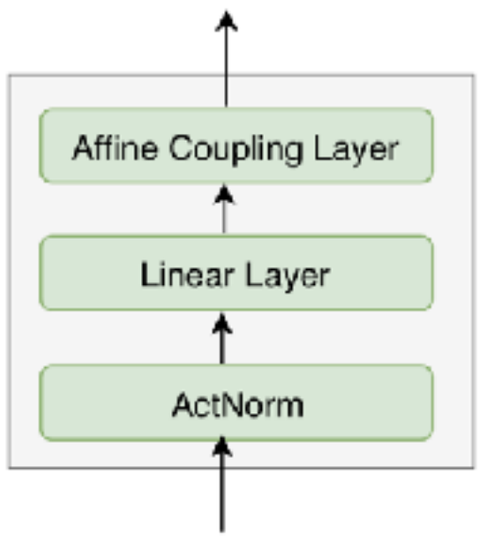
- Decoder: Transformer decoder w/o causal masking

$$q_\phi(\mathbf{z}|\mathbf{y}, \mathbf{x}) = \prod_{t=1}^{T} \mathcal{N}(\mathbf{z}_t|\mu_t(\mathbf{x}, \mathbf{y}), \sigma_t^2(\mathbf{x}, \mathbf{y}))$$

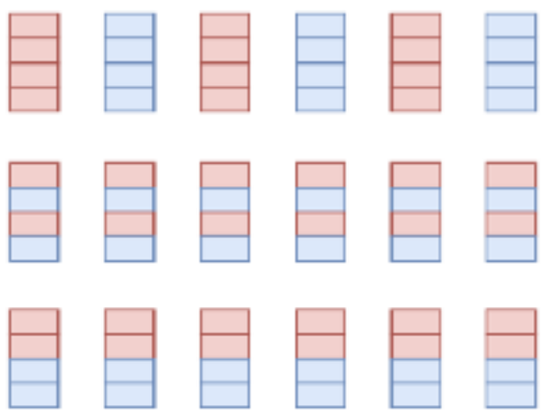
# Flow Architecture for Prior

- Actnorm (activation normalization layer): $\mathbf{z}'_t = \mathbf{s} \odot \mathbf{z}_t + \mathbf{b}.$
- Invertible Multi-head Linear Layers: $\mathbf{z}'_t = \mathbf{z}_t \mathbf{W},$ (W: [dz x dz])
- Affine Coupling Layers

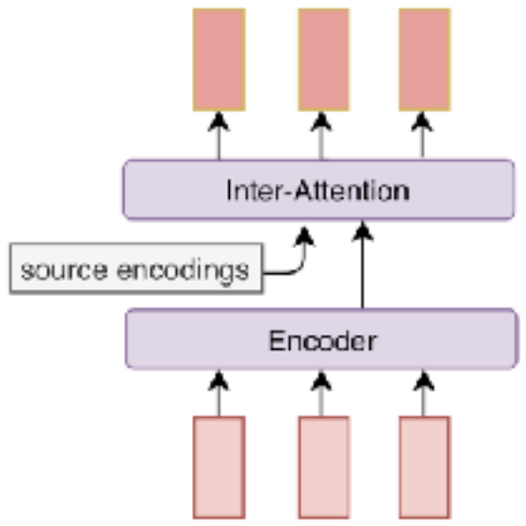
$$
\begin{aligned}
\mathbf{z}_a, \mathbf{z}_b &= \text{split}(\mathbf{z}) \\
\mathbf{z}'_a &= \mathbf{z}_a \\
\mathbf{z}'_b &= \text{s}(\mathbf{z}_a, \mathbf{x}) \odot \mathbf{z}_b + \text{b}(\mathbf{z}_a, \mathbf{x}) \\
\mathbf{z}' &= \text{concat}(\mathbf{z}'_a, \mathbf{z}'_b),
\end{aligned}
$$




(a) One step of flow.



(b) Coupling layer splits.




(c) NN function on the split of the coupling layer.

# Decoding Process

- **Argmax** Decoding

$$\begin{aligned} \mathbf{z}^* &= \operatorname*{argmax}_{\mathbf{z} \in \mathcal{Z}} p_\theta(\mathbf{z}|\mathbf{x}) \\ \mathbf{y}^* &= \operatorname*{argmax}_{\mathbf{y}} P_\theta(\mathbf{y}|\mathbf{z}^*, \mathbf{x}) \end{aligned}$$

- **Noisy Parallel Decoding (NPD)**: rescoring multiple samples by a pre-trained auto-regressive model.
- **Importance Weighted Decoding (IWD)**: rescoring multiple candidates by importance samples.

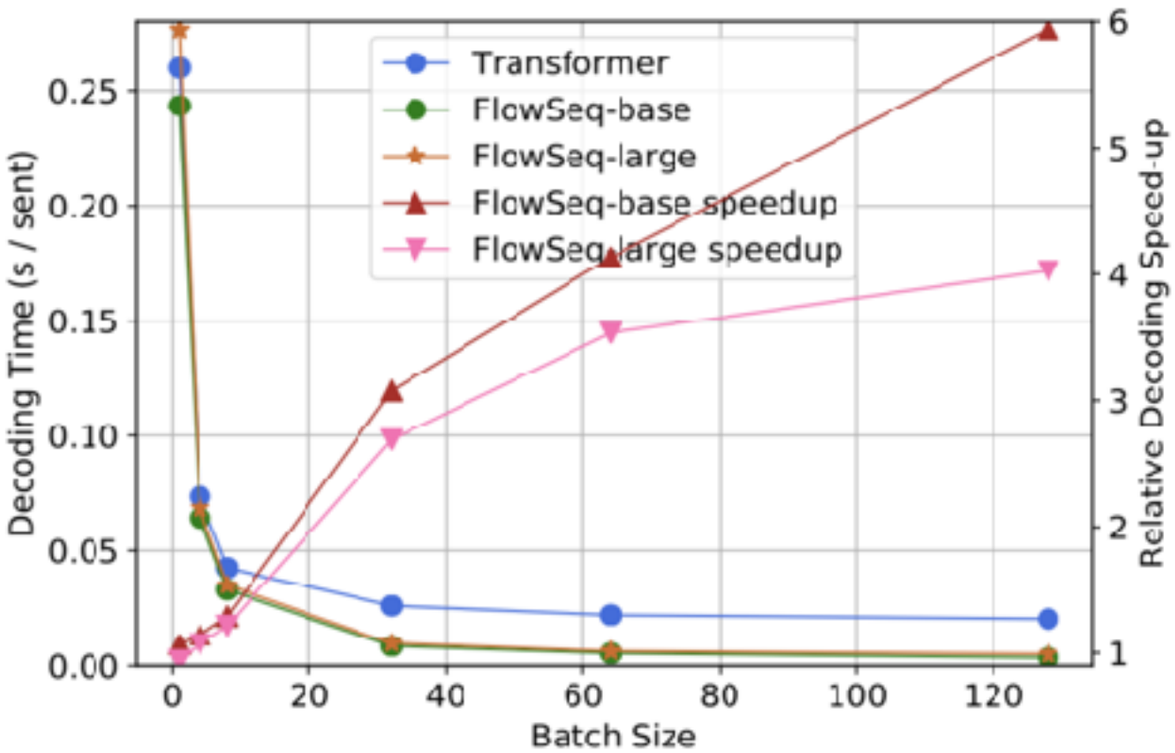
$$\begin{aligned} \mathbf{z}_i &\sim p_\theta(\mathbf{z}|\mathbf{x}), \forall i = 1, \ldots, N \\ \hat{\mathbf{y}}_i &= \operatorname*{argmax}_{\mathbf{y}} P_\theta(\mathbf{y}|\mathbf{z}_i, \mathbf{x}) \\ \mathbf{z}_i^{(k)} &\sim q_\phi(\mathbf{z}|\hat{\mathbf{y}}_i, \mathbf{x}), \forall k = 1, \ldots, K \\ P(\hat{\mathbf{y}}_i|\mathbf{x}) &\approx \frac{1}{K} \sum_{k=1}^{K} \frac{P_\theta(\hat{\mathbf{y}}_i|\mathbf{z}_i^{(k)}, \mathbf{x}) p_\theta(\mathbf{z}_i^{(k)}|\mathbf{x})}{q_\phi(\mathbf{z}_i^{(k)}|\hat{\mathbf{y}}_i, \mathbf{x})} \end{aligned}$$

# Experiments

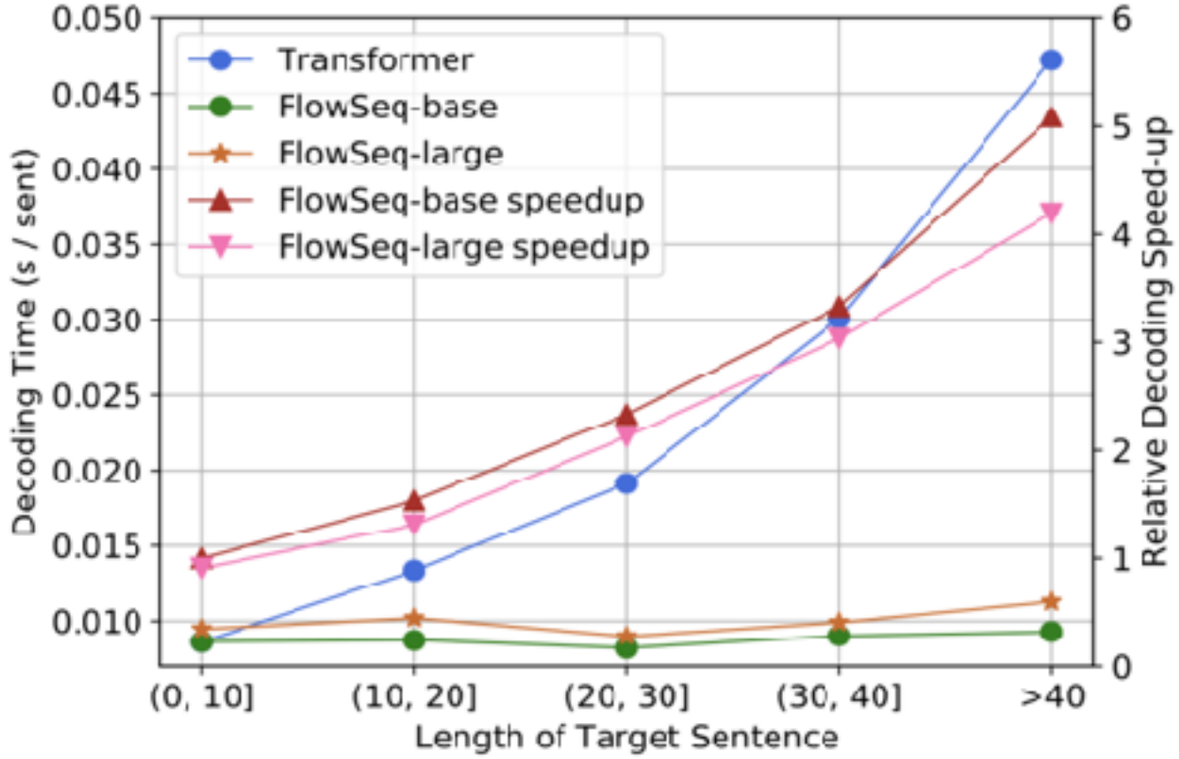
- MT benchmark datasets:
  - IWSLT 2014 EN-DE
  - WMT14 EN-DE, DE-EN
  - WMT16 EN-RO, RO-EN

| Models | WMT2014 EN-DE | WMT2014 DE-EN | WMT2016 EN-RO | WMT2016 RO-EN |
|---|---|---|---|---|
| Autoregressive Methods | | | | |
| Transformer-base | 27.30 | – | – | – |
| Our Implementation | 27.16 | 31.44 | 32.92 | 33.09 |
| Raw Data | | | | |
| CMLM (refinement 1) | 10.88 | – | 20.24 | – |
| CMLM (refinement 4) | 22.06 | – | 30.89 | – |
| CMLM (refinement 10) | **24.65** | – | **32.53** | – |
| FlowSeq-large (Argmax) | 20.85 | 25.40 | 29.86 | 30.69 |
| FlowSeq-large (IWD $n = 15$) | 22.94 | 27.16 | 31.08 | 32.03 |
| FlowSeq-large (NPD $n = 15$) | 23.14 | 27.71 | 31.97 | 32.46 |
| FlowSeq-large (NPD $n = 30$) | 23.64 | **28.29** | 32.35 | **32.91** |
| Knowledge Distillation | | | | |
| NAT w/ FT (Argmax) | 17.69 | 21.47 | 27.29 | 29.06 |
| NAT w/ FT (NPD $n = 10$) | 18.66 | 22.42 | 29.02 | 31.44 |
| NAT-IR (refinement 1) | 13.91 | 16.77 | 24.45 | 25.73 |
| NAT-IR (refinement 10) | 21.61 | 25.48 | 29.32 | 30.19 |
| NAT-REG (NPD $n = 9$) | 24.61 | 28.90 | – | – |
| CMLM (refinement 1) | 18.12 | 22.26 | 23.65 | 22.78 |
| CMLM (refinement 4) | 26.08 | 30.11 | 31.78 | 31.76 |
| CMLM (refinement 10) | **26.92** | **30.86** | **32.42** | **33.06** |
| FlowSeq-large (Argmax) | 23.72 | 28.39 | 29.73 | 30.72 |
| FlowSeq-large (IWD $n = 15$) | 24.70 | 29.44 | 31.02 | 31.97 |
| FlowSeq-large (NPD $n = 15$) | 25.03 | 30.48 | 31.89 | 32.43 |
| FlowSeq-large (NPD $n = 30$) | 25.31 | 30.68 | 32.20 | 32.84 |

# Decoding Speed

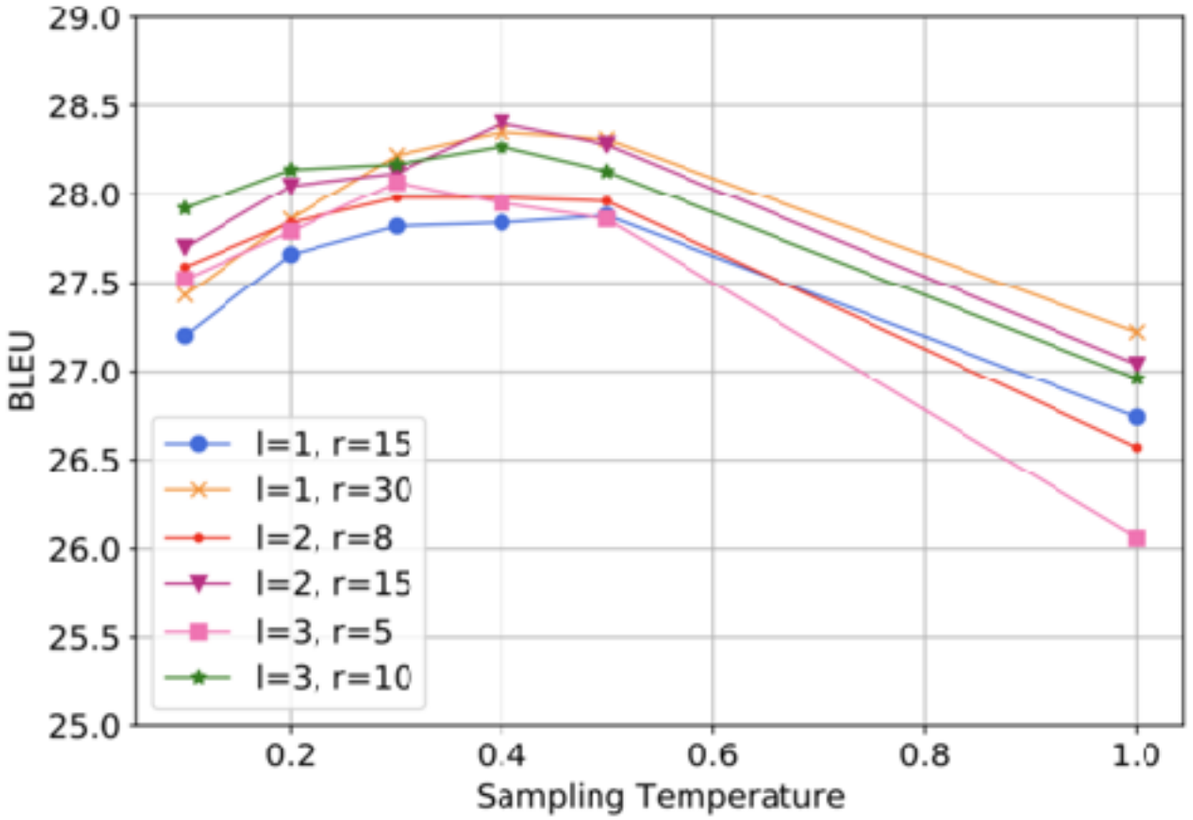



(a) batch size

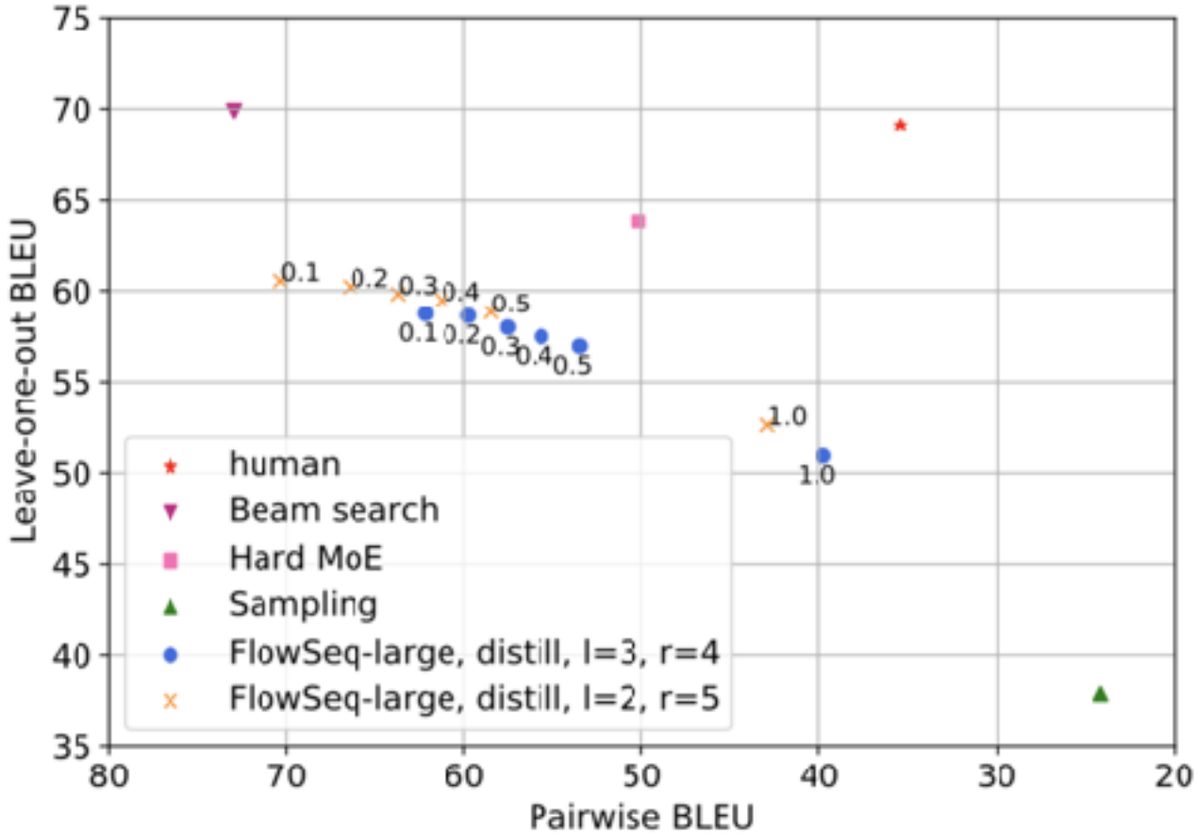



(b) target length

# Analysis of Translations




(c) Rescoring




(d) Diversity

# An Example

| | |
|---|---|
| Source | Es kann nicht erklären, weshalb die National Security Agency Daten ber das Privatleben von Amerikanern sammelt und warum Whistleblower bestraft werden, die staatliches Fehlverhalten offenlegen. |
| Ground Truth | And, most recently, it cannot excuse the failure to design a simple website more than three years since the Affordable Care Act was signed into law. |
| Sample 1 | And recently, it cannot apologise for the inability to design a simple website in the more than three years since the adoption of Affordable Care Act. |
| Sample 2 | And recently, it cannot excuse the inability to design a simple website in more than three years since the adoption of Affordable Care Act. |
| Sample 3 | Recently, it cannot excuse the inability to design a simple website in more than three years since the Affordable Care Act has passed. |

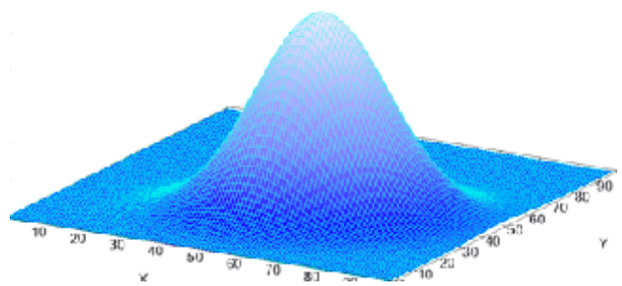
# Conclusion

# Conclusion

- Normalizing flows for unsupervised learning

$$X = f_\theta^{-1}(Z)$$

$$Z = f_\theta(X)$$

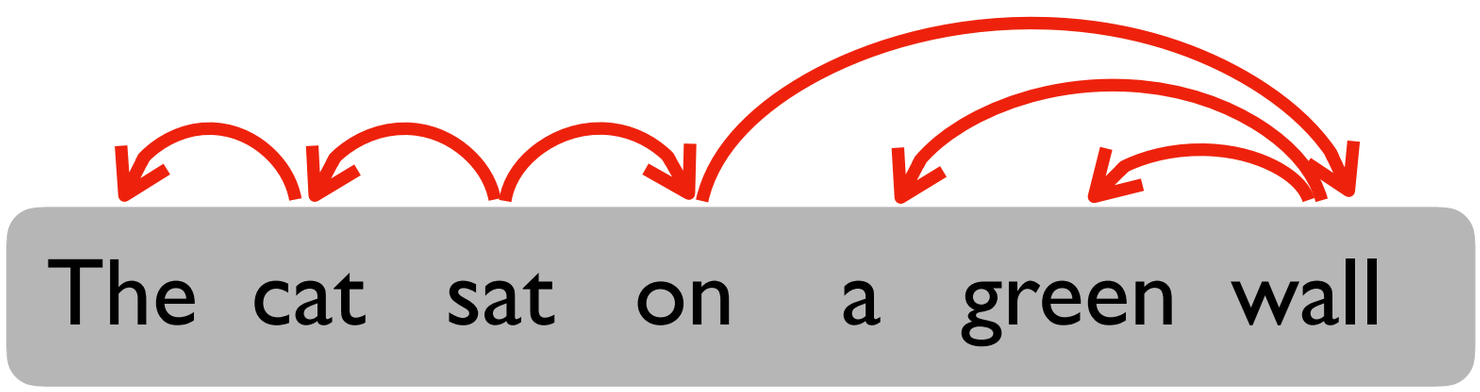


- Learning of bilingual lexicons
- Learning of latent structure
- Learning of sequence-to-sequence models

# Thank You! Questions?

DeMa-BWE

https://github.com/violet-zct/DeMa-BWE




https://github.com/jxhe/struct-learning-with-flow

https://github.com/XuezheMax/flowseq