Carnegie Mellon University
School of Computer Science

More is Less?
Non-parametric Language Models and Efficiency

Graham Neubig
Carnegie Mellon University

Based on Work by Junxian He w/ Taylor Berg-Kirkpatrick

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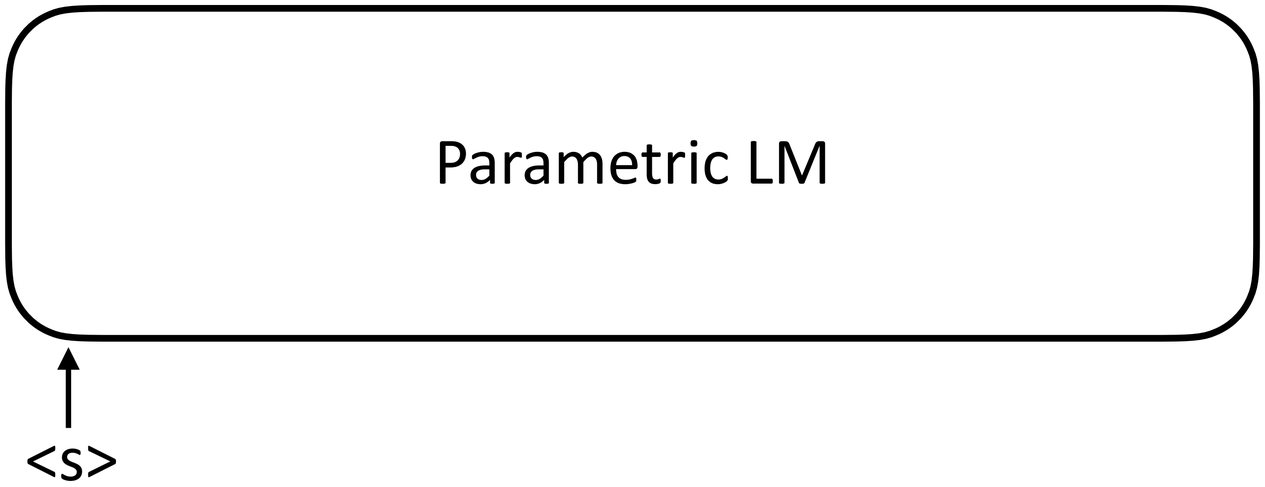
Parametric Language Models



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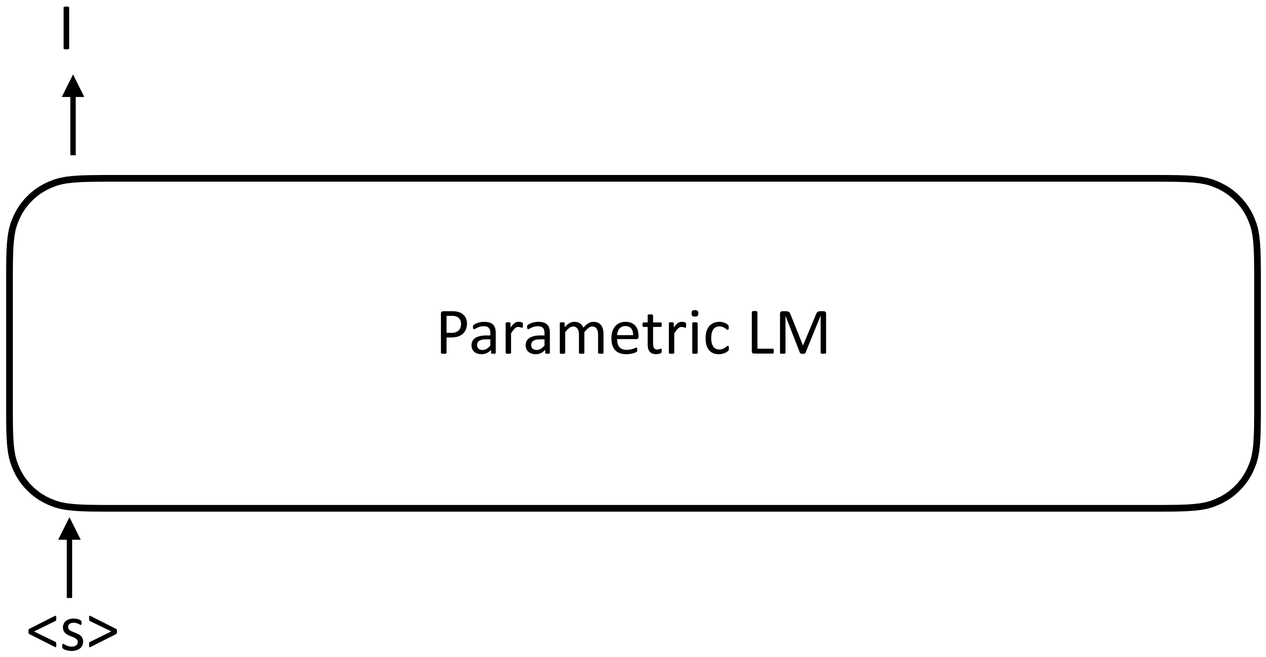

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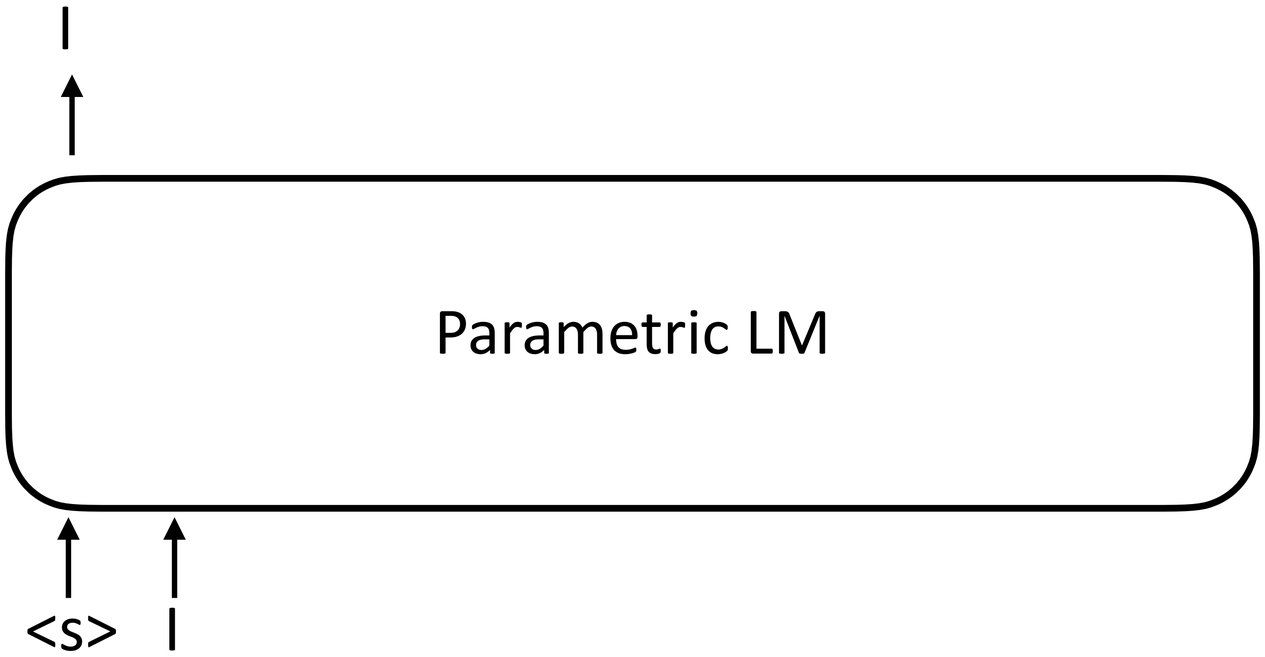
Parametric Language Models



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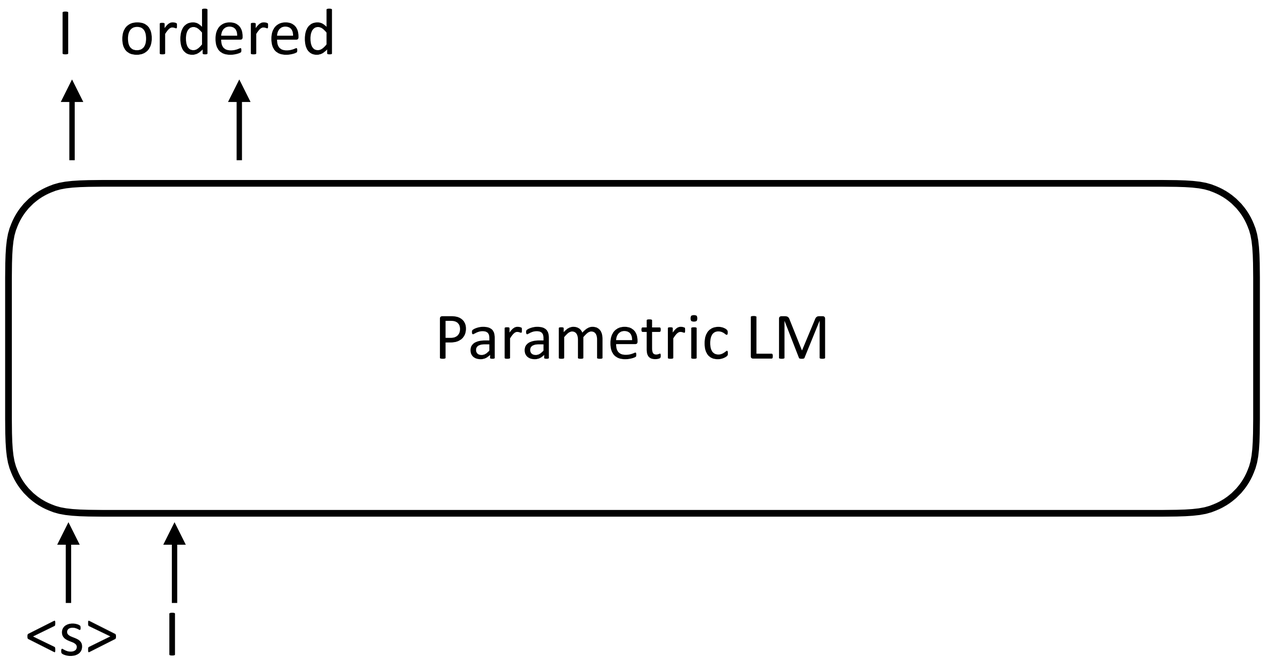

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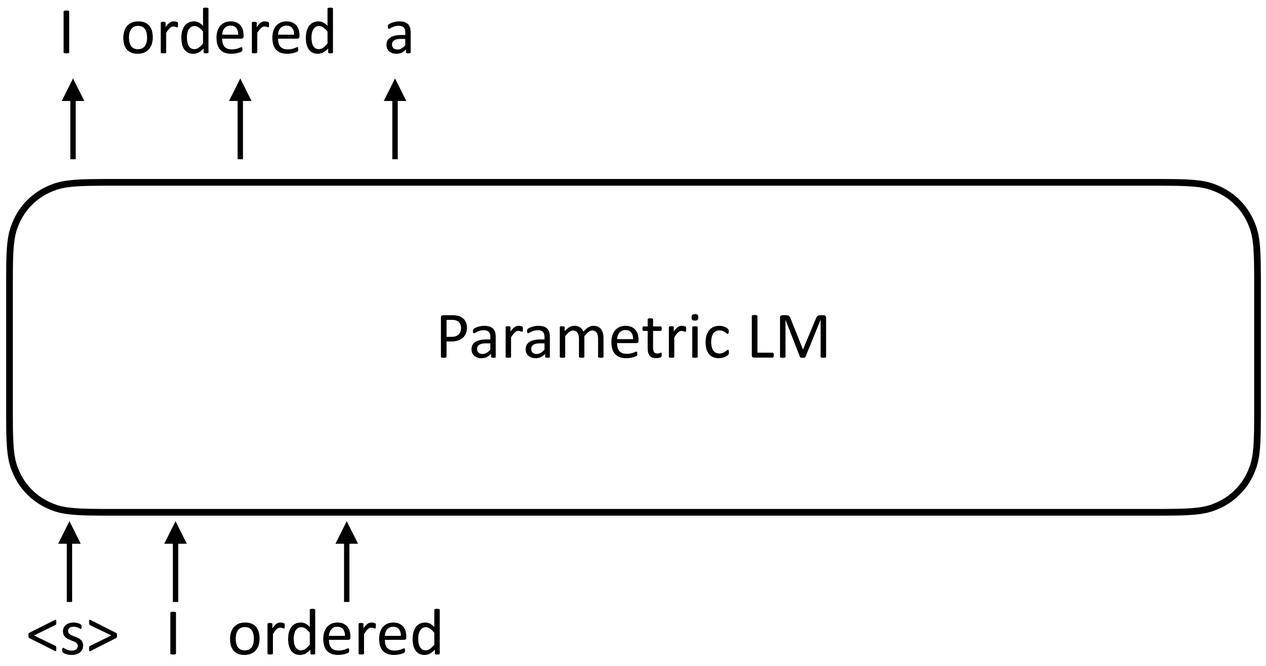

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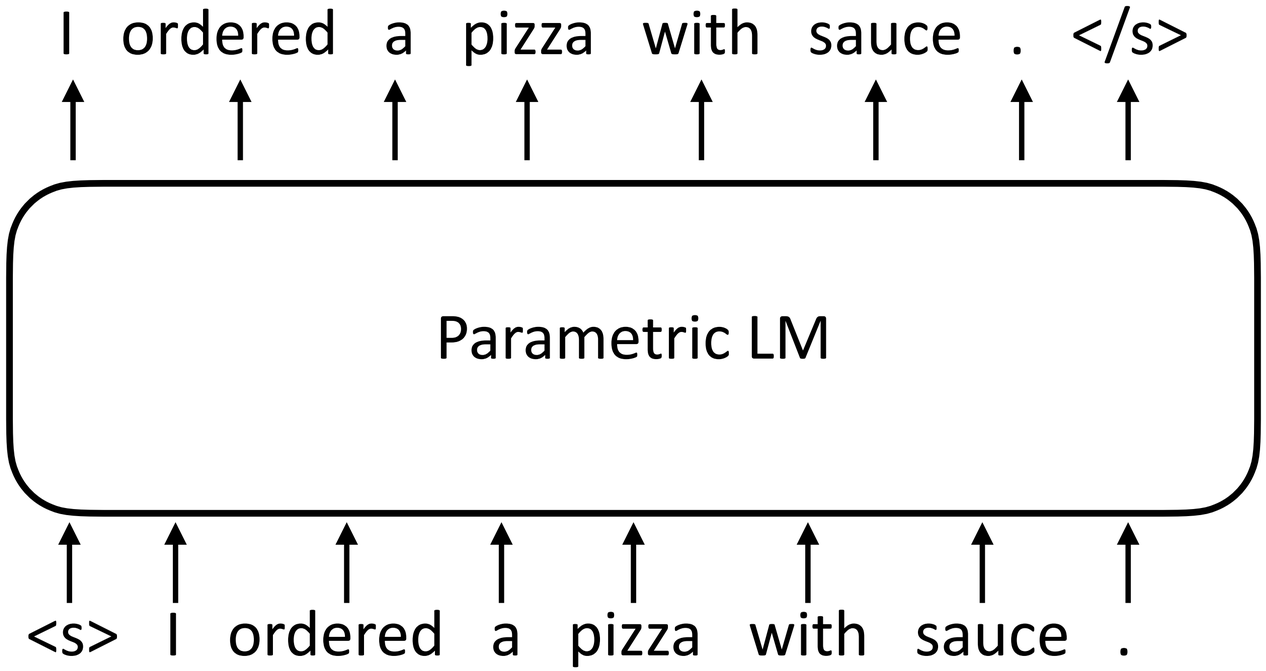

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Non-Parametric Language Models

Non-Parametric LM

Non-parametric datastore (typically training dataset)

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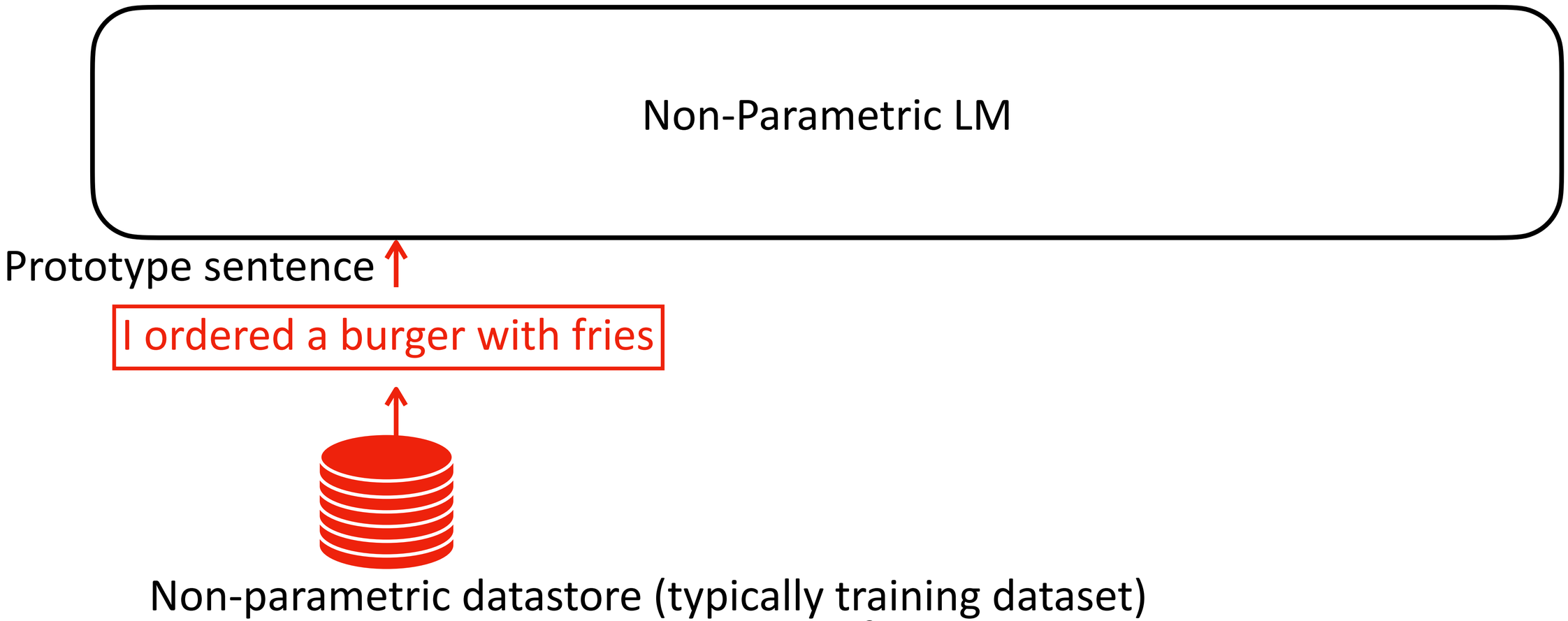
Non-Parametric Language Models



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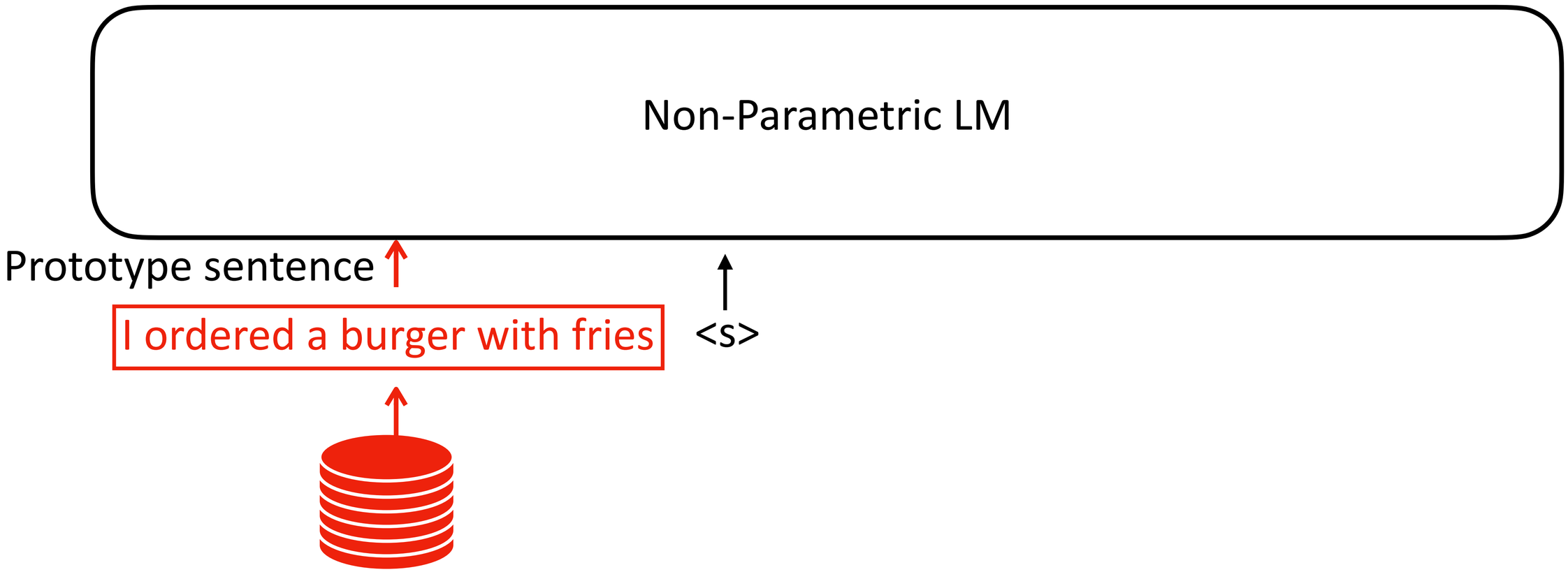

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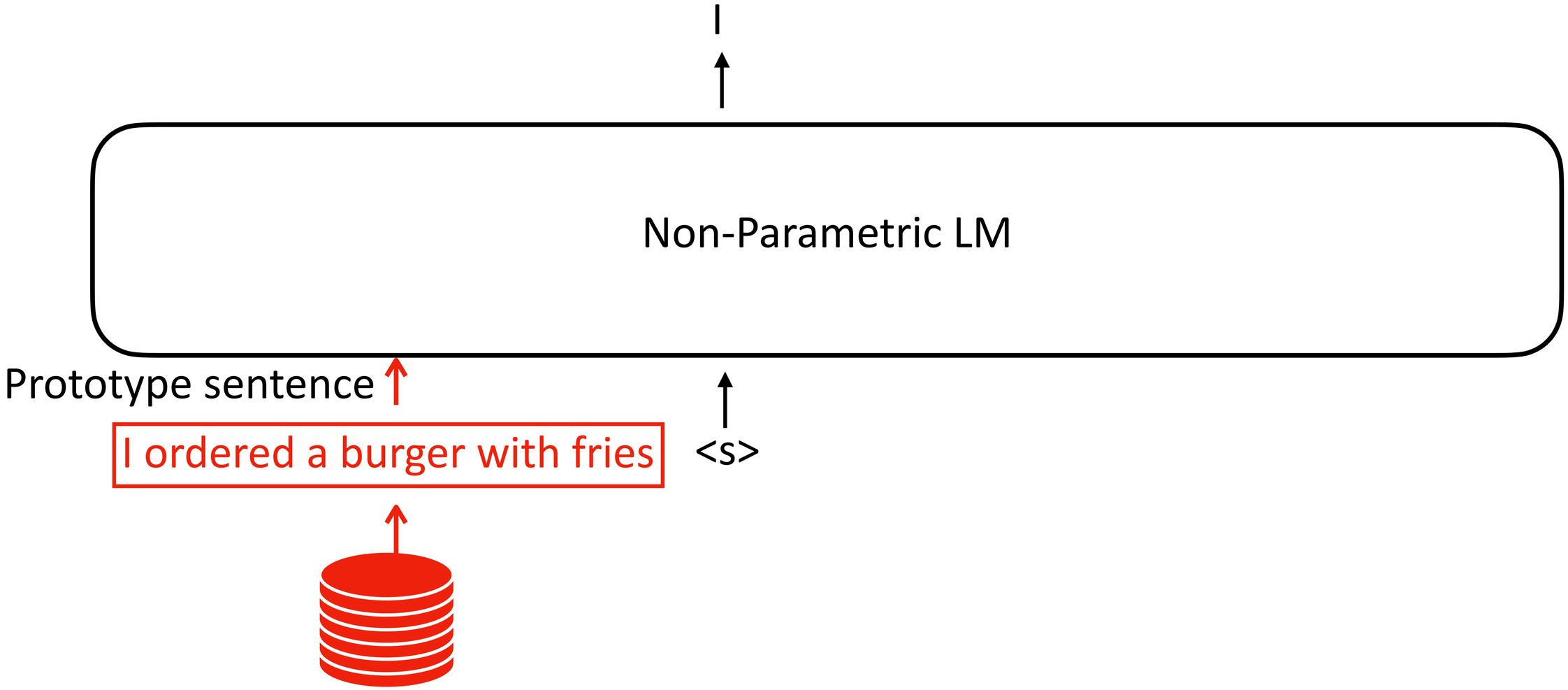

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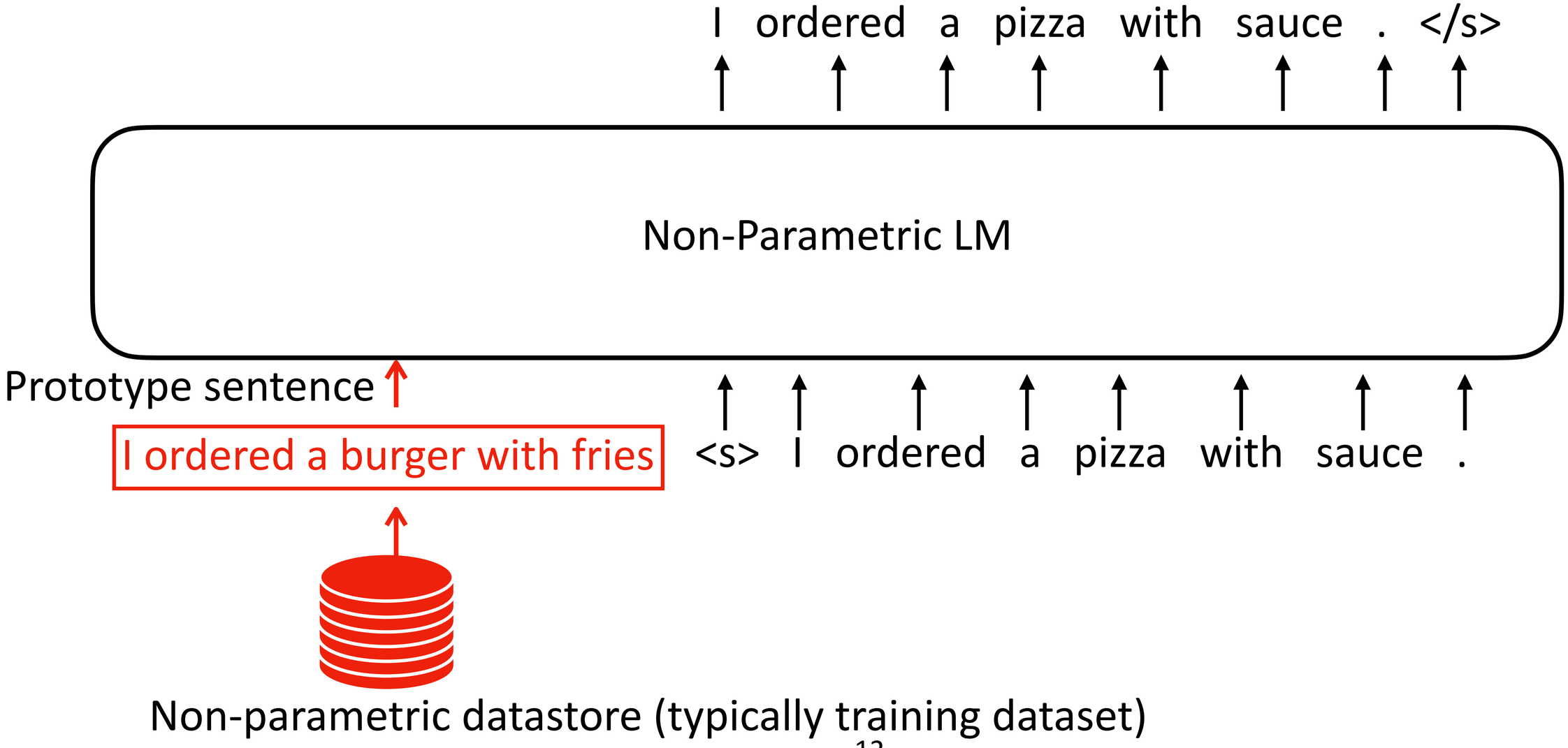

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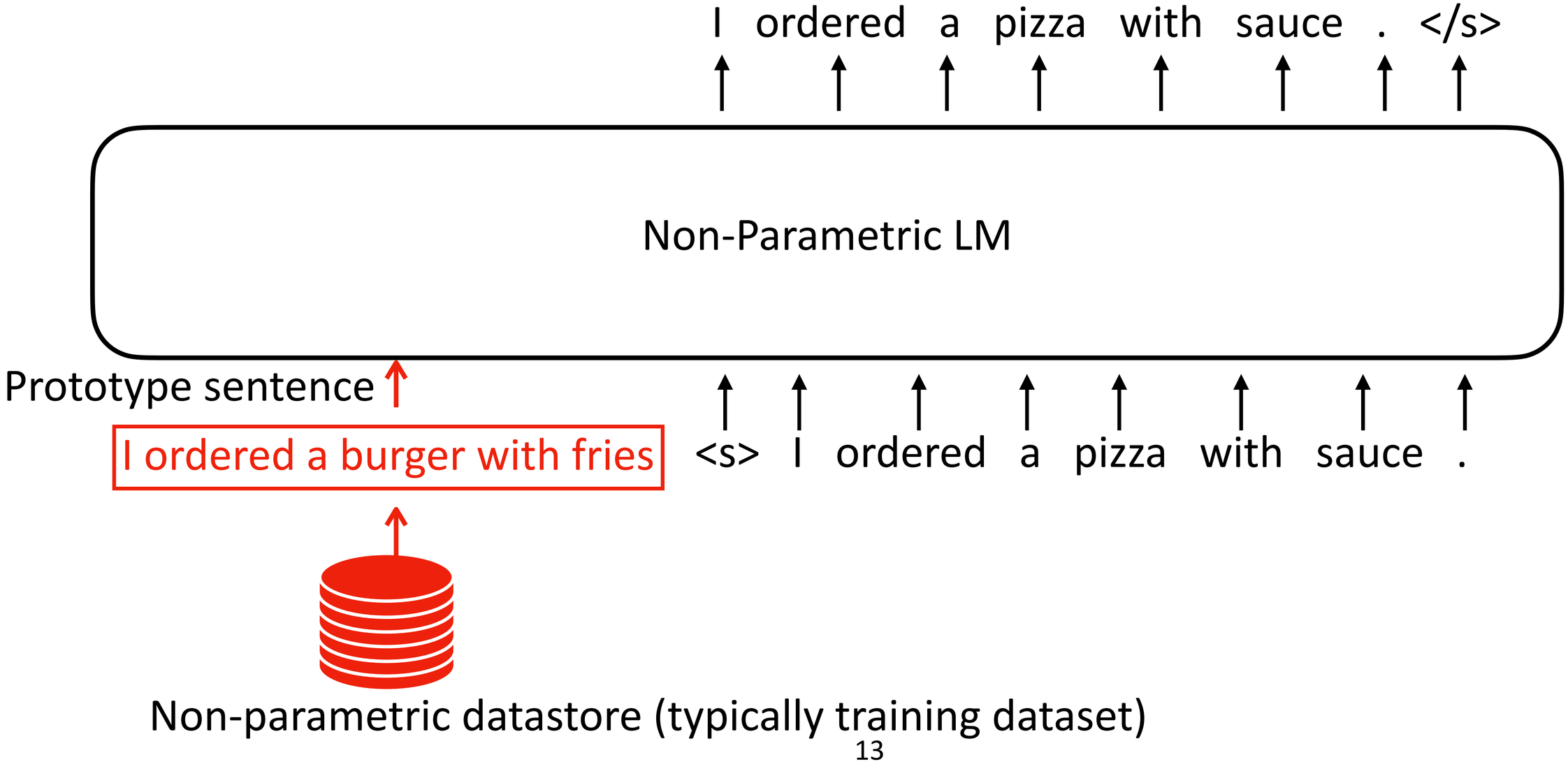

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A Human Processing Analogy

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A Human Processing Analogy

Our Language Ability/ Knowledge

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A Human Processing Analogy

Our Language Ability/ Knowledge

Our Language Ability/ Knowledge + Wikipedia/Google

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A (Very Incomplete) Survey of Neural Non-parametric Models for NLP

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A (Very Incomplete) Survey of Neural Non-parametric Models for NLP

- **Count-based non-parametric data stores:**
  - *Neural Machine Translation with External Phrase Memory. Tang et al. 2016.*
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Non-Parametric Language Models: Pros/Cons

Pros

- Mitigate pressure on the parametric models
- Improved interpretability in the modeling process

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Non-Parametric Language Models: Pros/Cons

Pros

- Mitigate pressure on the parametric models
- Improved interpretability in the modeling process

Cons

- In almost all cases, large parametric datastore leads to significant issues with memory and speed efficiency at test time

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A Concrete Example: Prototype-based Language Models (Guu et al. TACL 2018)

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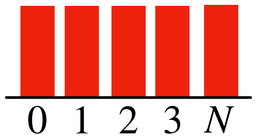
Previous Approach

Prototype distribution



$p(\mathbf{t})$ **Uniform**

Guu et al. 2018

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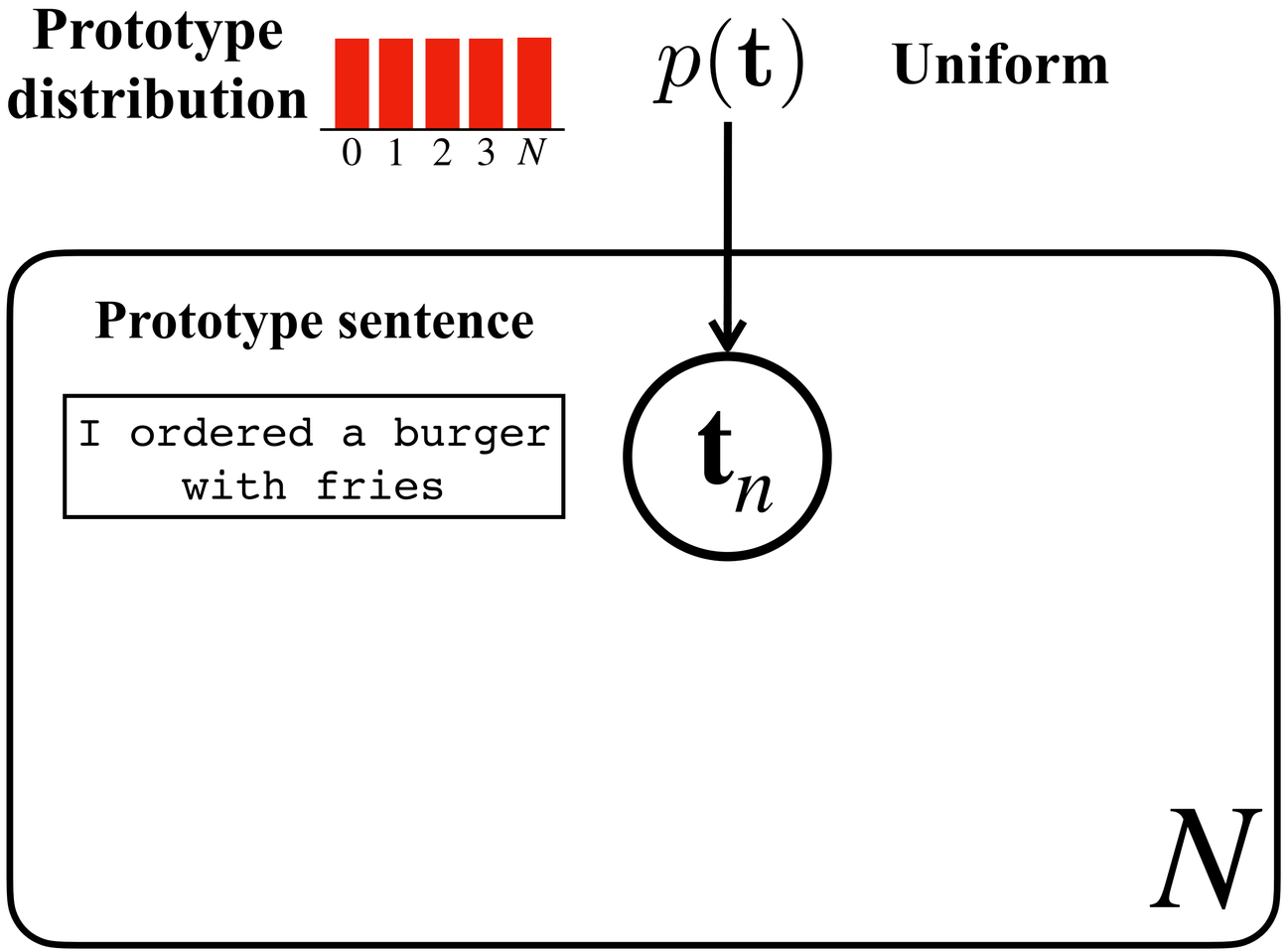
Previous Approach



Guu et al. 2018

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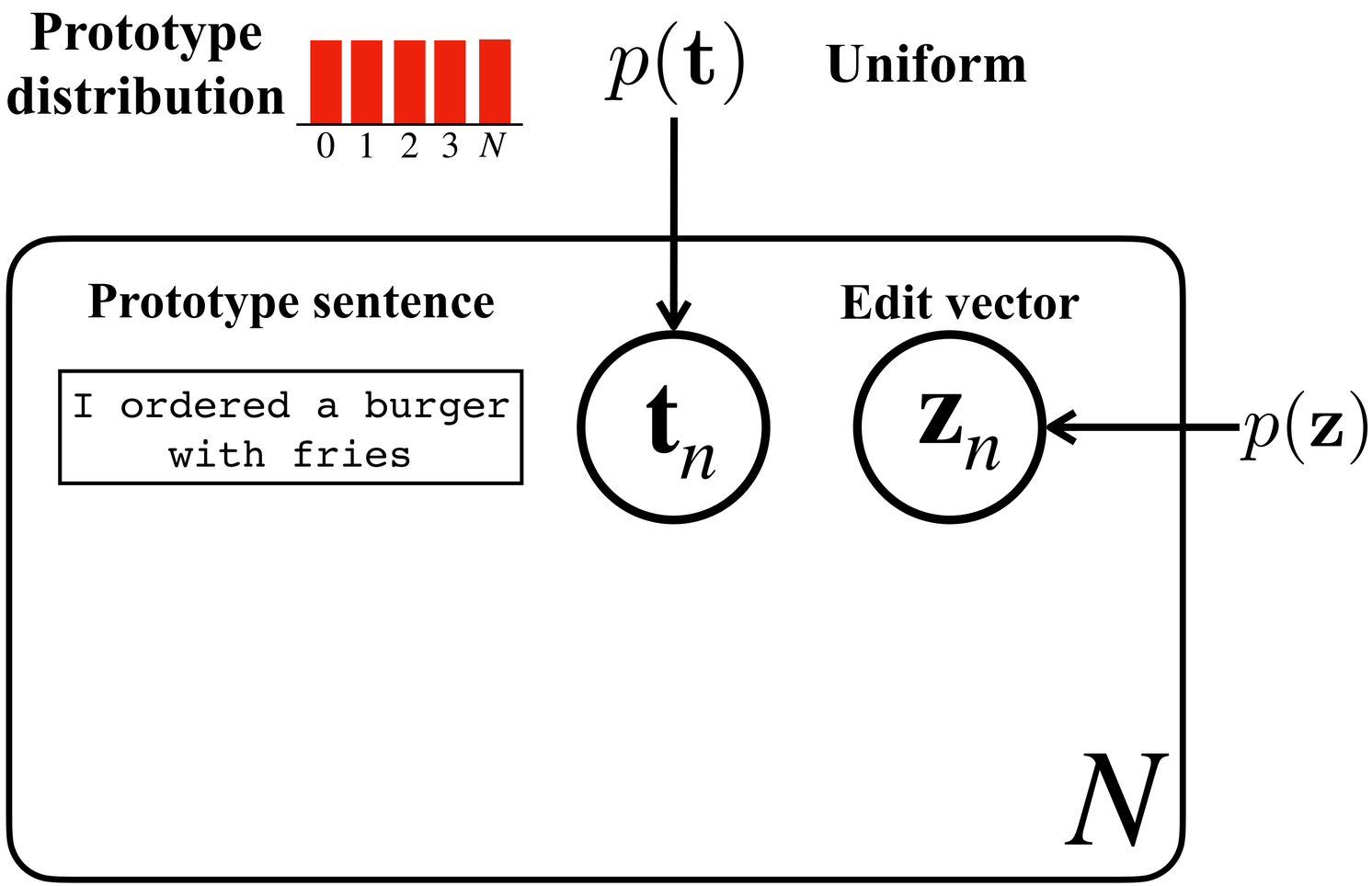
Previous Approach



Guu et al. 2018

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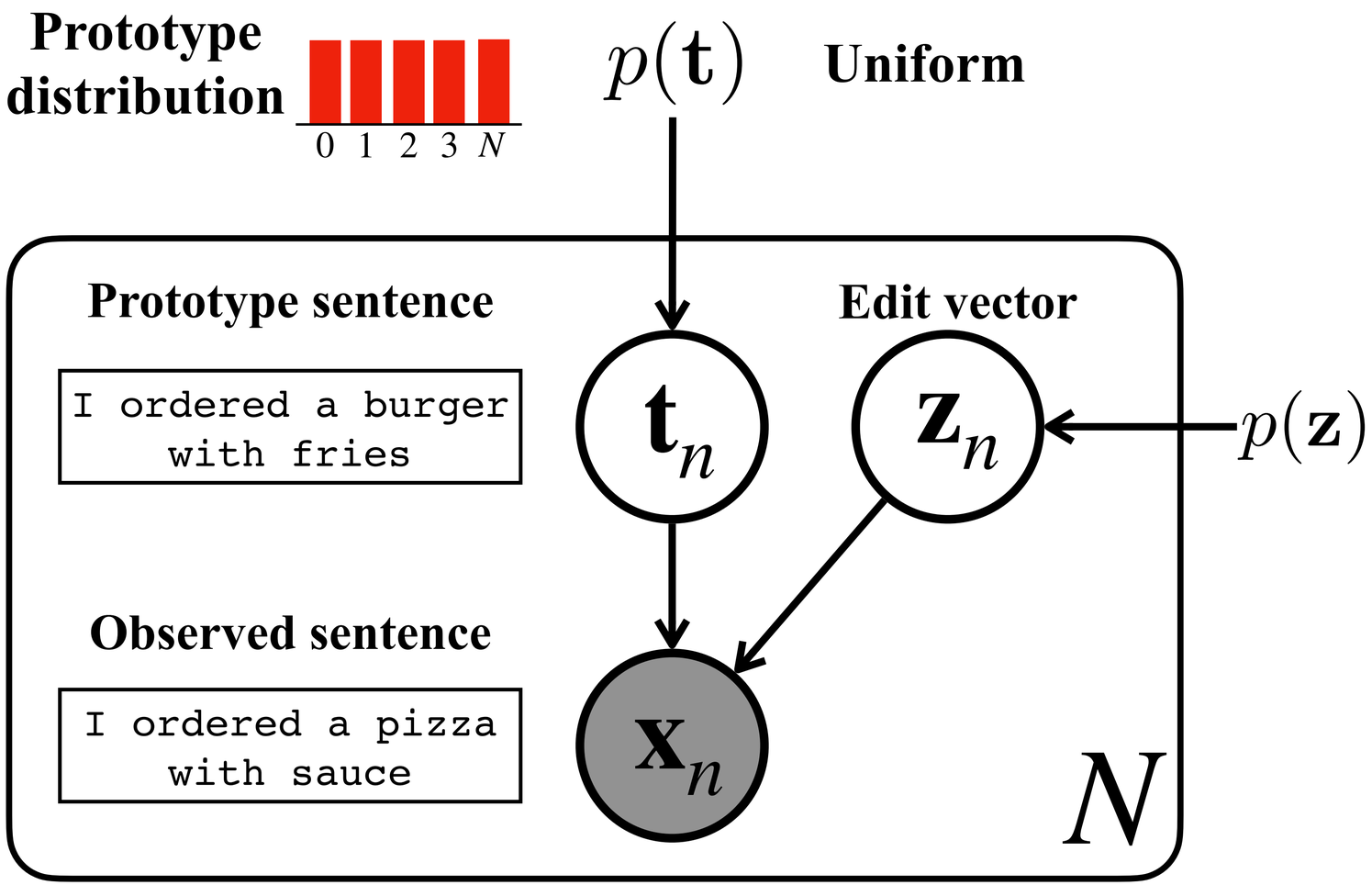

Guu et al. 2018

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Proposed Model:
Sparse Prototypes for Text Generation
(He et al. NeurIPS 2020)

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Prototypes can be Sparse

Prototype Sentence

I ordered a burger with fries

Data Examples

I ordered a pizza with sauce

I ordered a turkey with sauce

I ordered a sandwich with fries and coke

I ordered a lobster roll with oysters and spicy sauce

Guu et al. 2018

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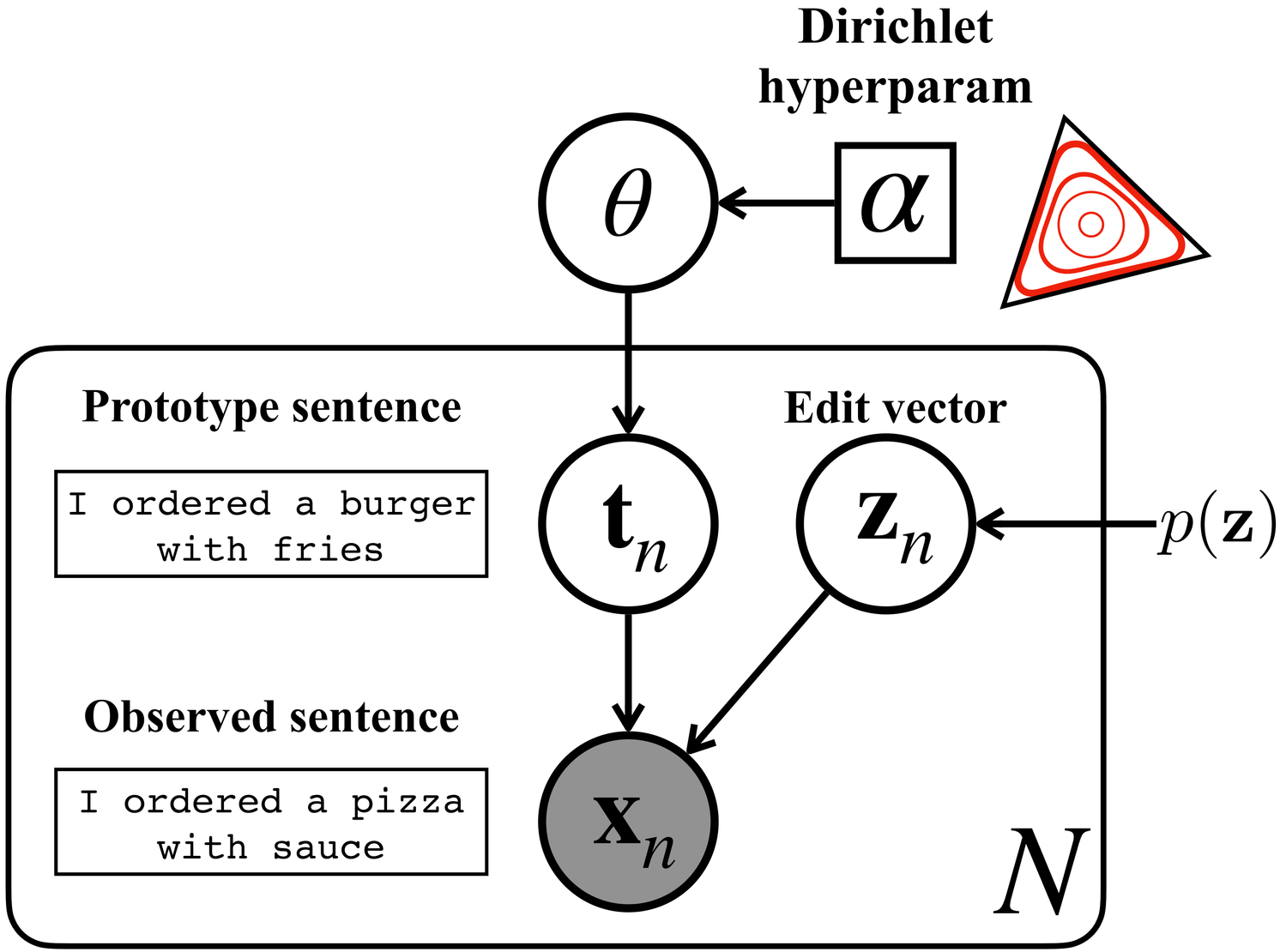
Sparse Neural Editor



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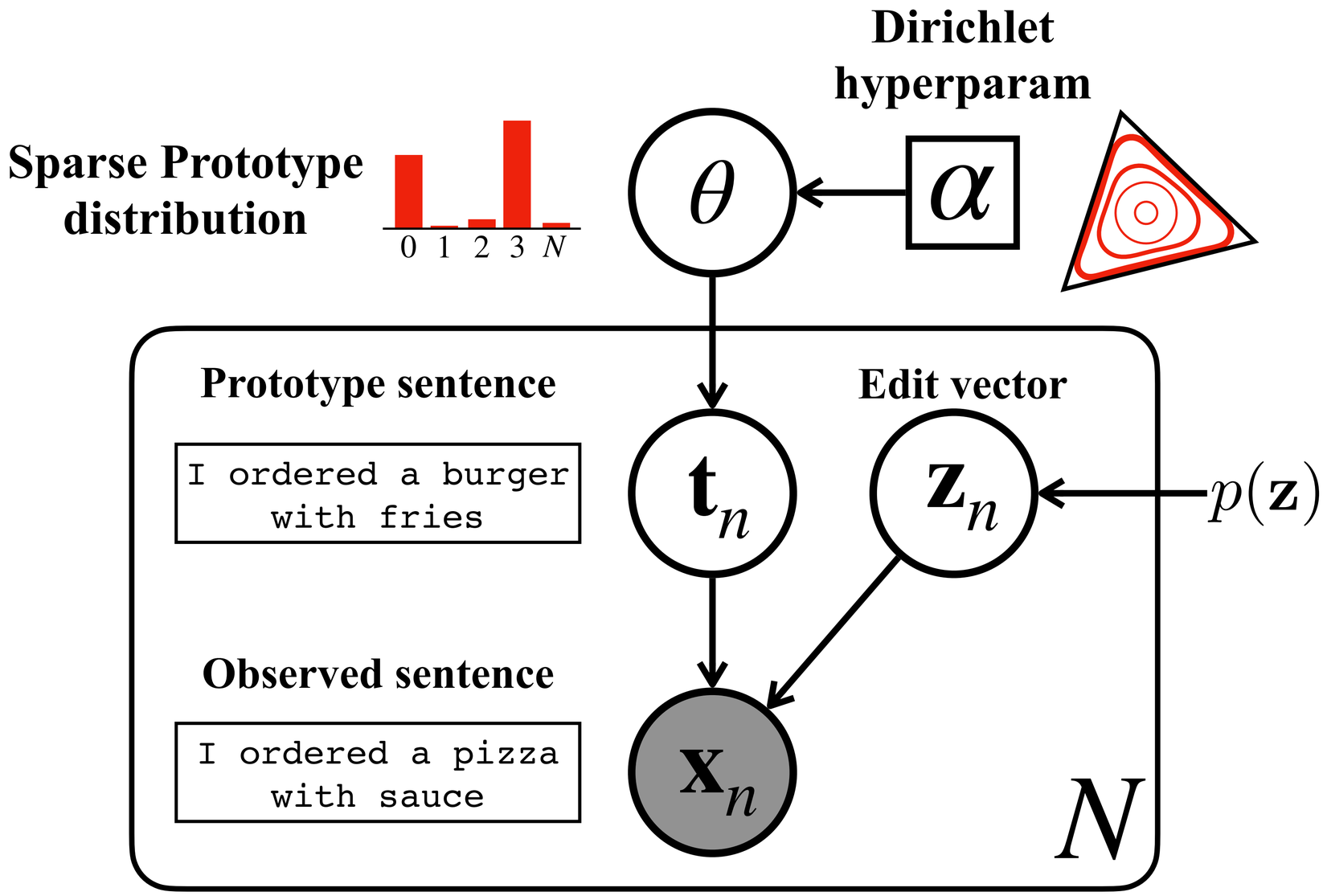

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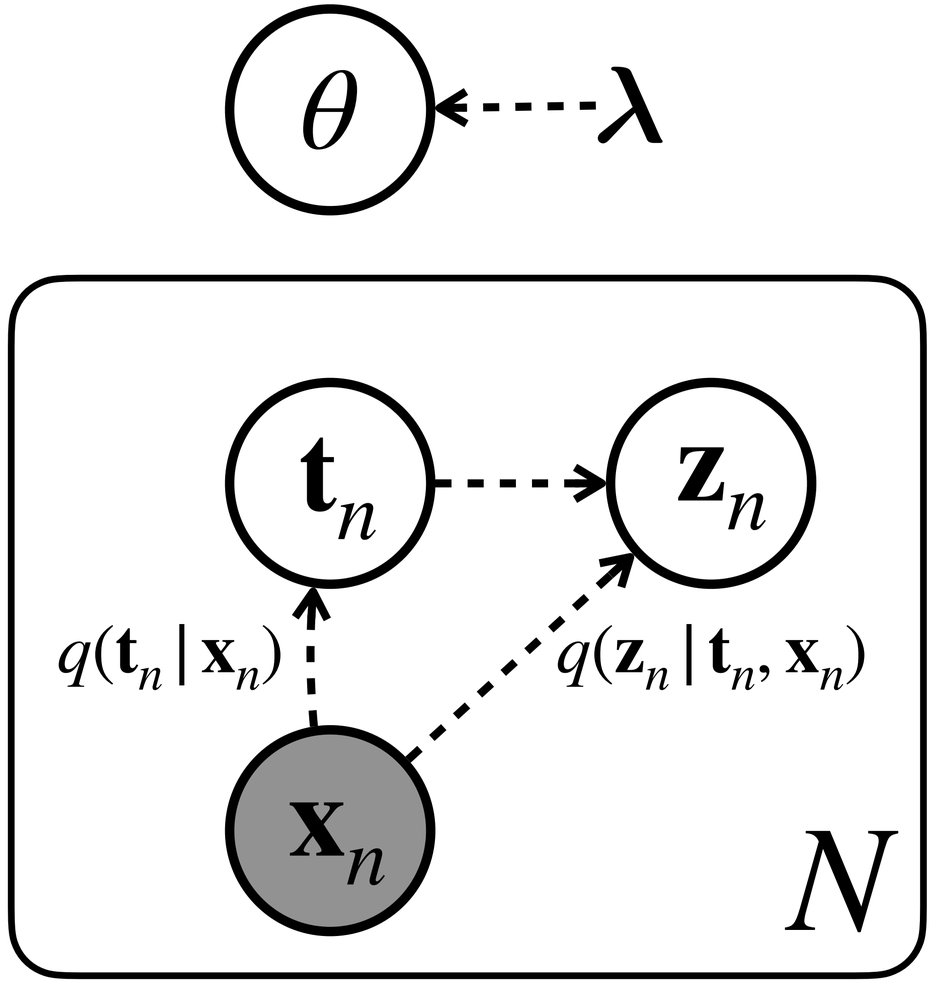
Learning and Inference

$$\log p(\mathbf{x}) \geq \mathcal{L}_{\text{ELBO}}$$

$$= \mathbb{E}_{q(\mathbf{t},\mathbf{z},\theta|\mathbf{x})} \log p(\mathbf{x}|\mathbf{t},\mathbf{z},\theta) - D_{\text{KL}}(q(\mathbf{t},\mathbf{z},\theta)||p(\mathbf{t},\mathbf{z},\theta))$$

Approximate posterior



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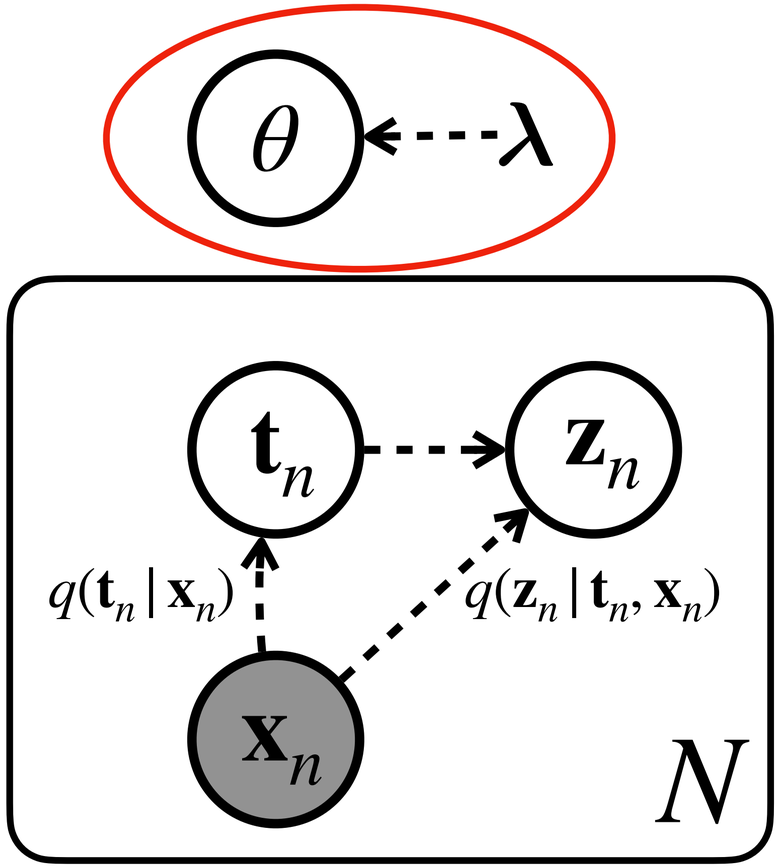
The Approximate Posterior



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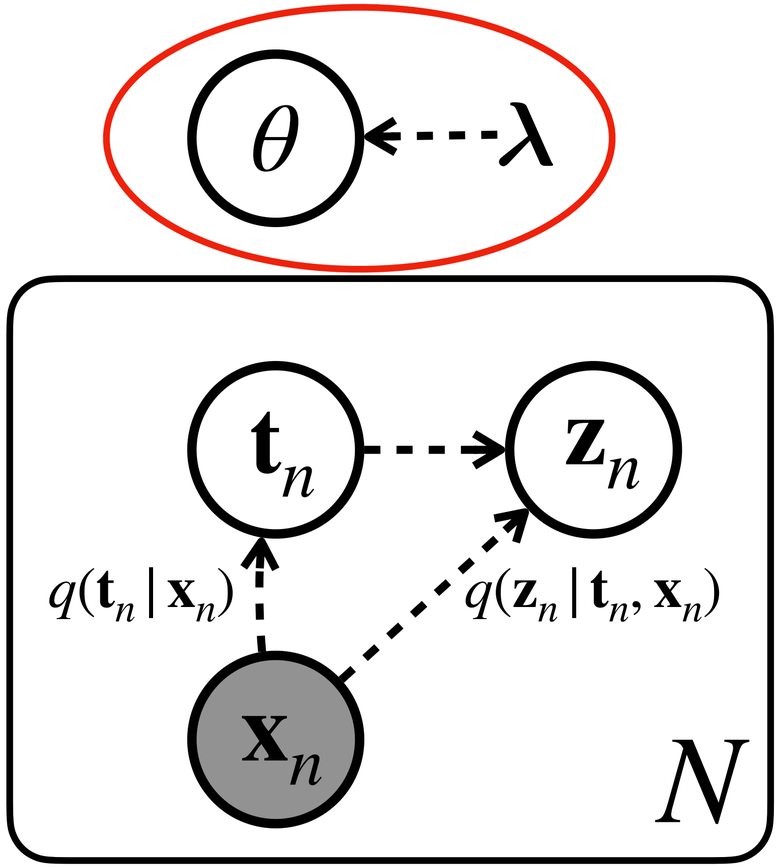
The Approximate Posterior



$$q(\theta) = \mathrm{Dir}(\theta; \boldsymbol{\lambda})$$

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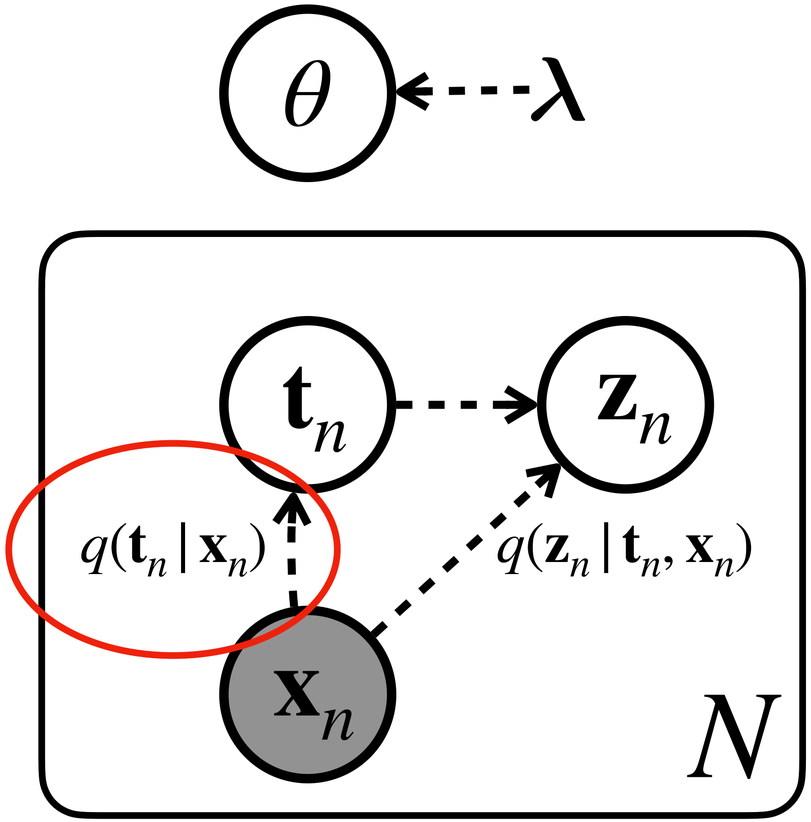
The Approximate Posterior



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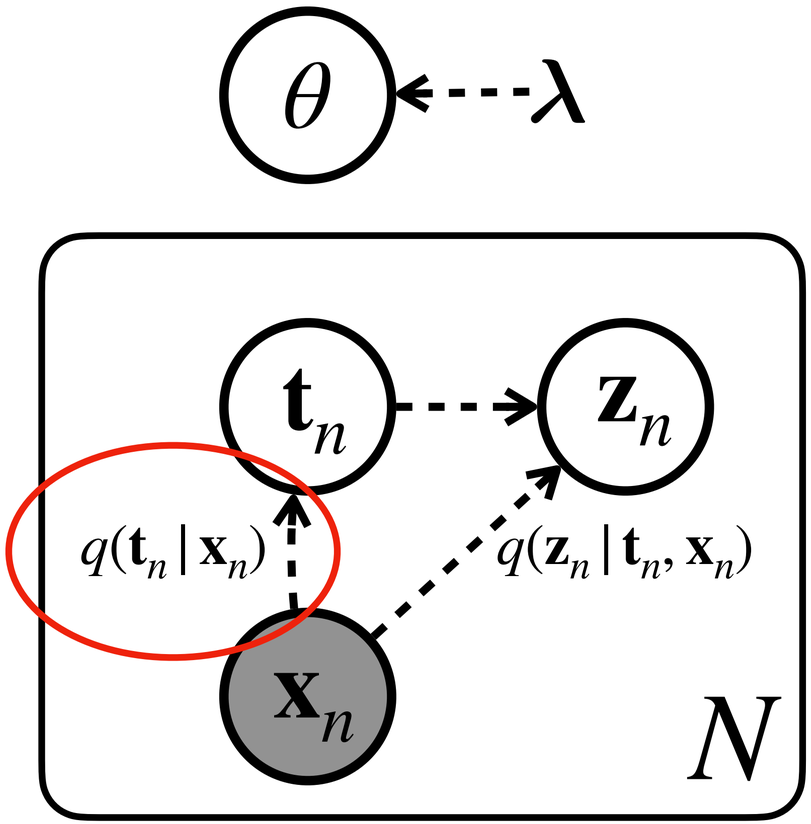
The Approximate Posterior



$$q(\mathbf{t} = \mathbf{x}_k|\mathbf{x}) \propto \begin{cases} \exp\left(h(\mathbf{x}_k, \mathbf{x})/\mu\right) & \text{if } \mathbf{x}_k \neq \mathbf{x} \\ 0 & \text{if } \mathbf{x}_k = \mathbf{x}, \end{cases}$$

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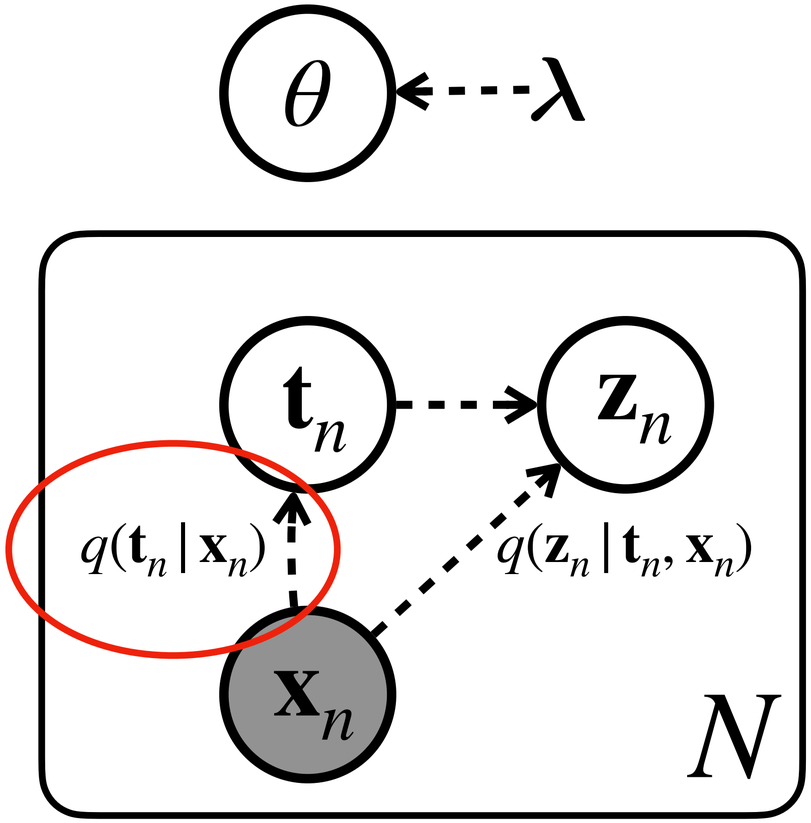
The Approximate Posterior



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$$h(\mathbf{x}_k, \mathbf{x}) = \texttt{Embed}(\mathbf{x}_k)^\top \boldsymbol{W} \texttt{Embed}(\mathbf{x})$$

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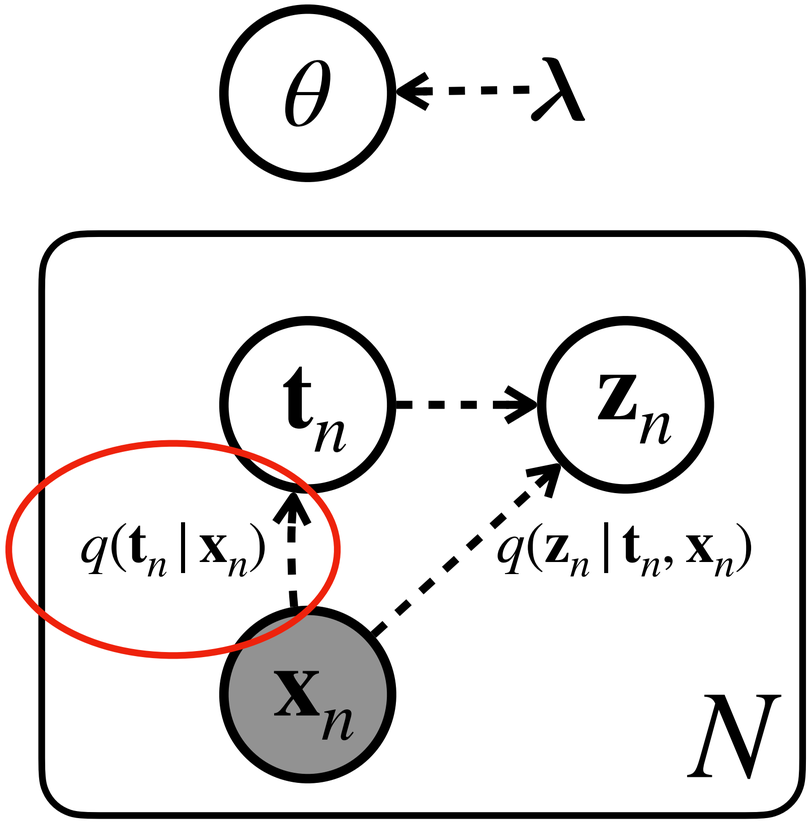
The Approximate Posterior



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BERT

Data example x

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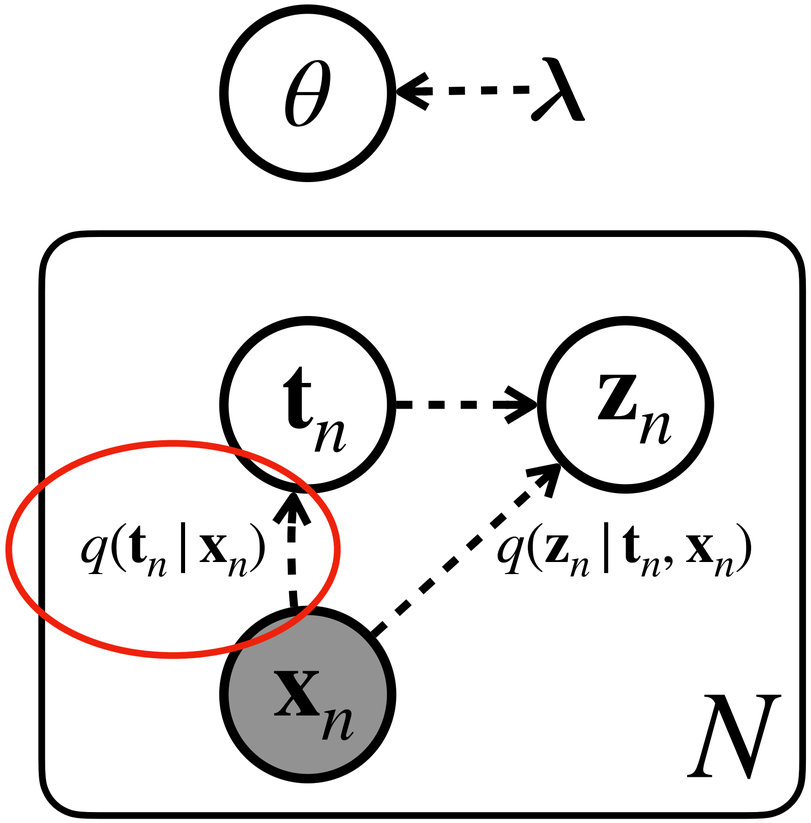
The Approximate Posterior



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BERT

Data example x

BERT

Prototype x_k

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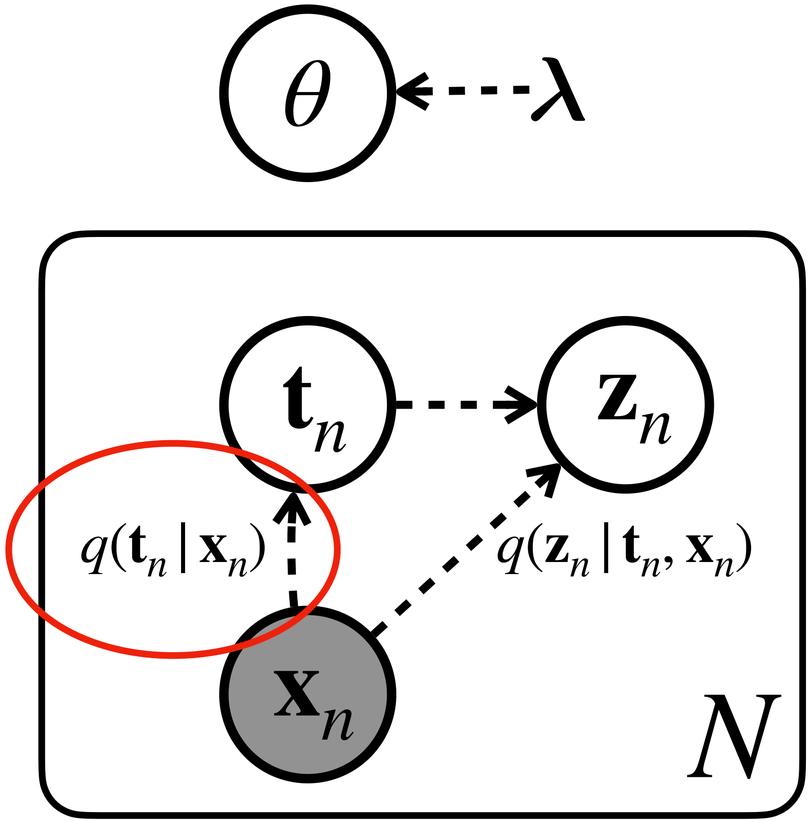
The Approximate Posterior



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BERT

Data example x

BERT

Prototype x_k

Only the linear transformation is learned while BERT is fixed. We use REINFORCE algorithm to propagate gradients over discrete prototype variables

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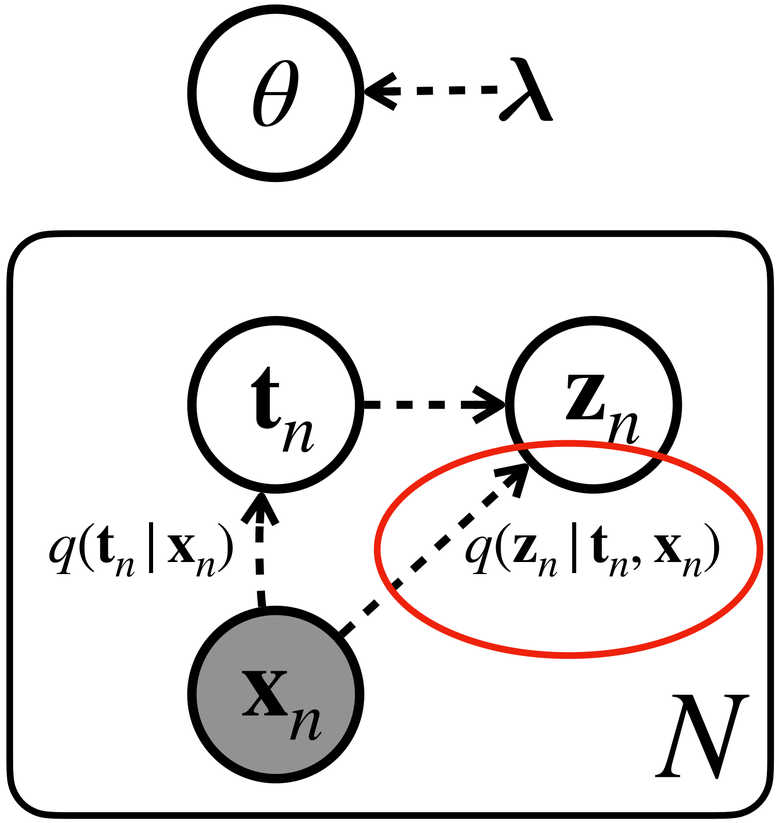
The Approximate Posterior



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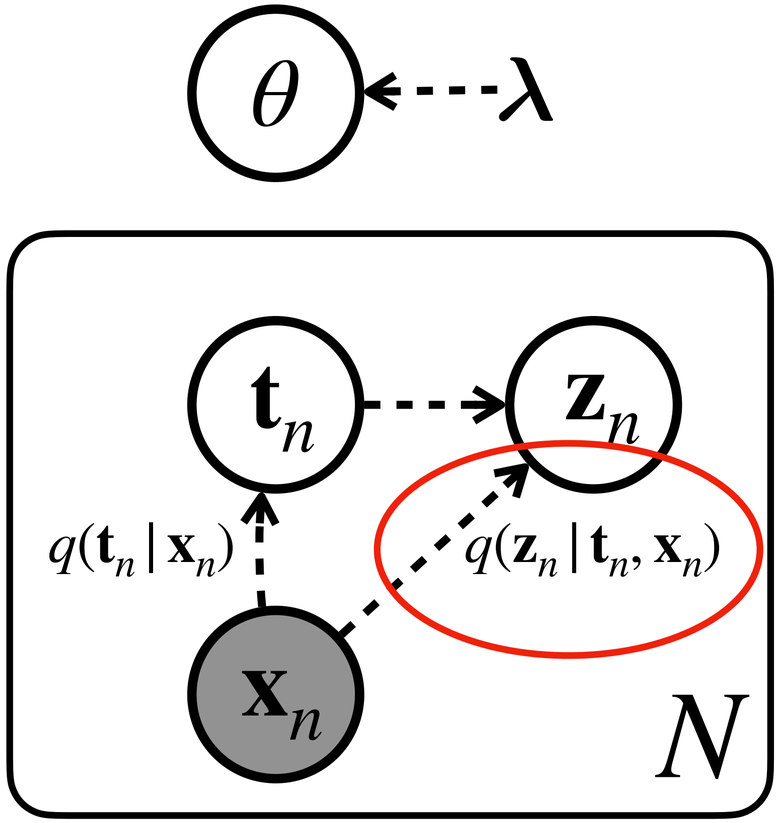

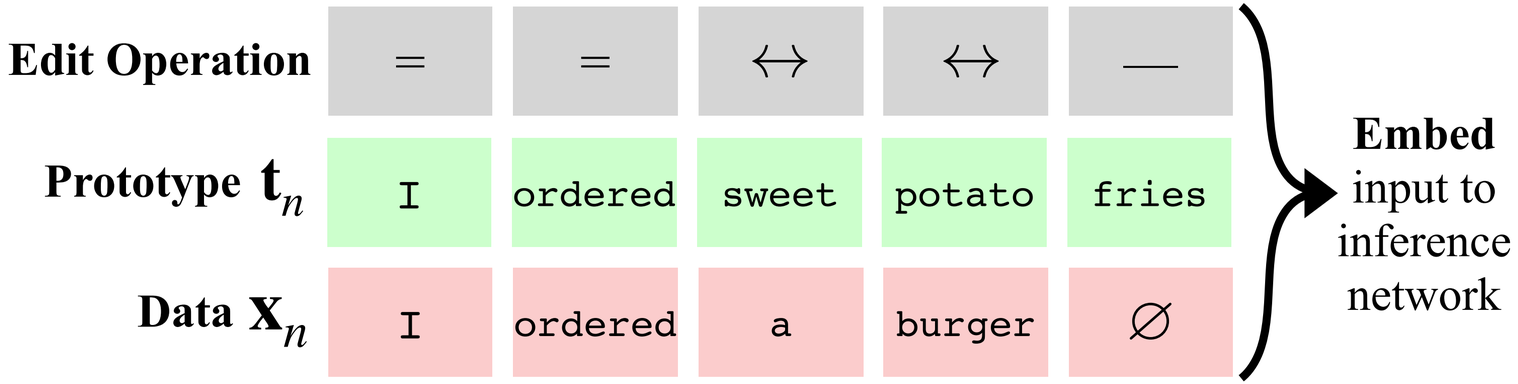

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Experiments

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Experiments

- Datasets
  - MSCOCO image caption (40K training)
  - Yelp restaurant reviews (17M training)

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Perplexity Results

Yelp Large	Yelp Medium	Yelp Large	
prototypes: 779	prototypes: 1.5k	prototypes: 17M	2K

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Perplexity Results

Yelp Large

prototypes: 779

Yelp Medium

prototypes: 1.5k

prototypes: 17M

2K

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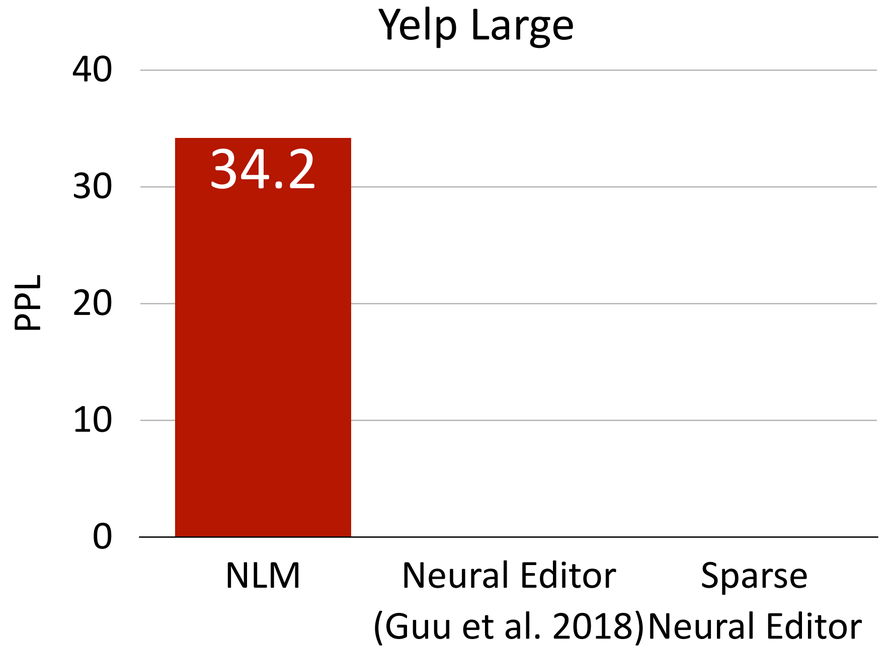
Perplexity Results

Yelp Large

Yelp Medium



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prototypes: 1.5k

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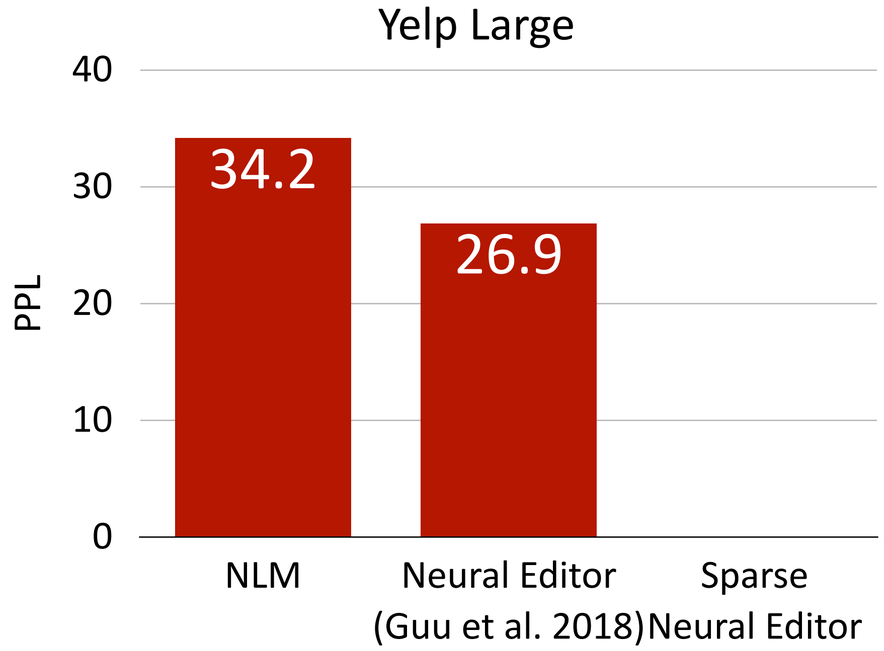
Perplexity Results

Yelp Large

Yelp Medium



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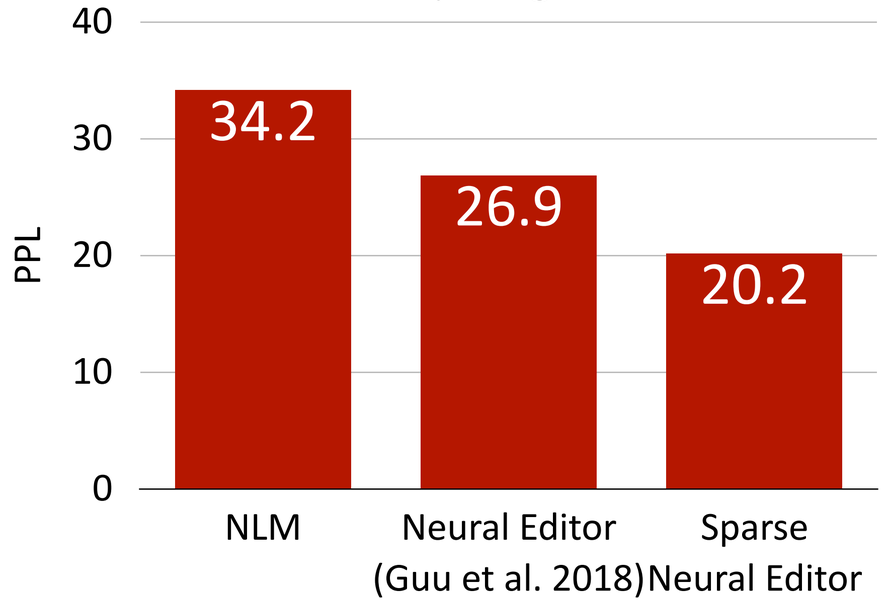

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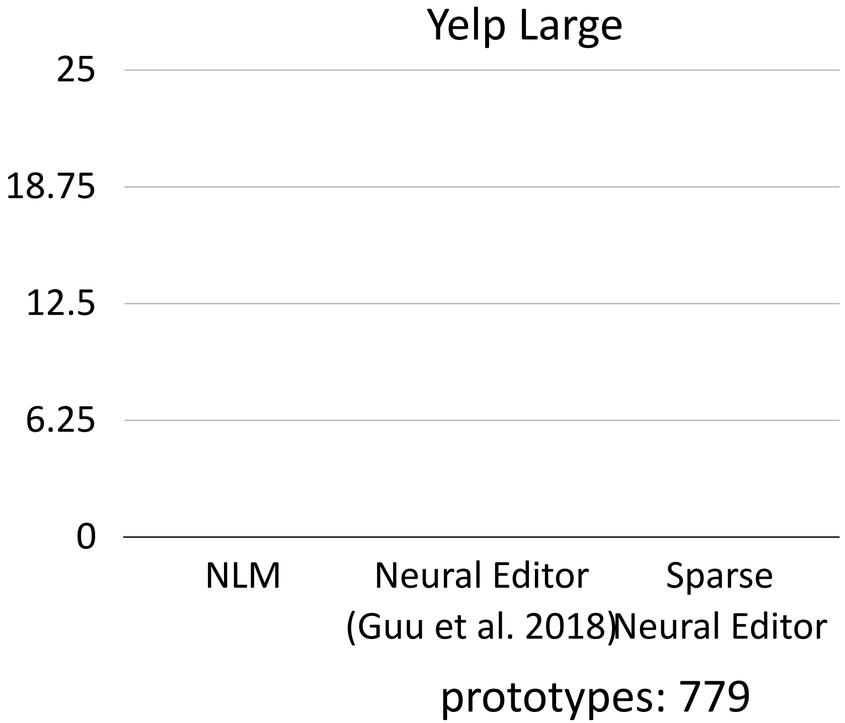

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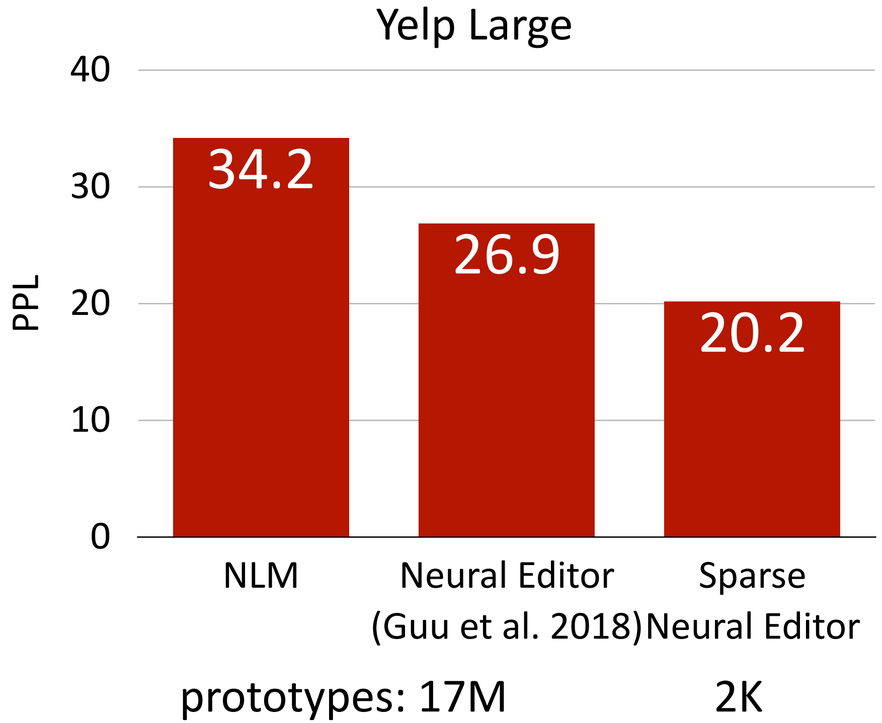

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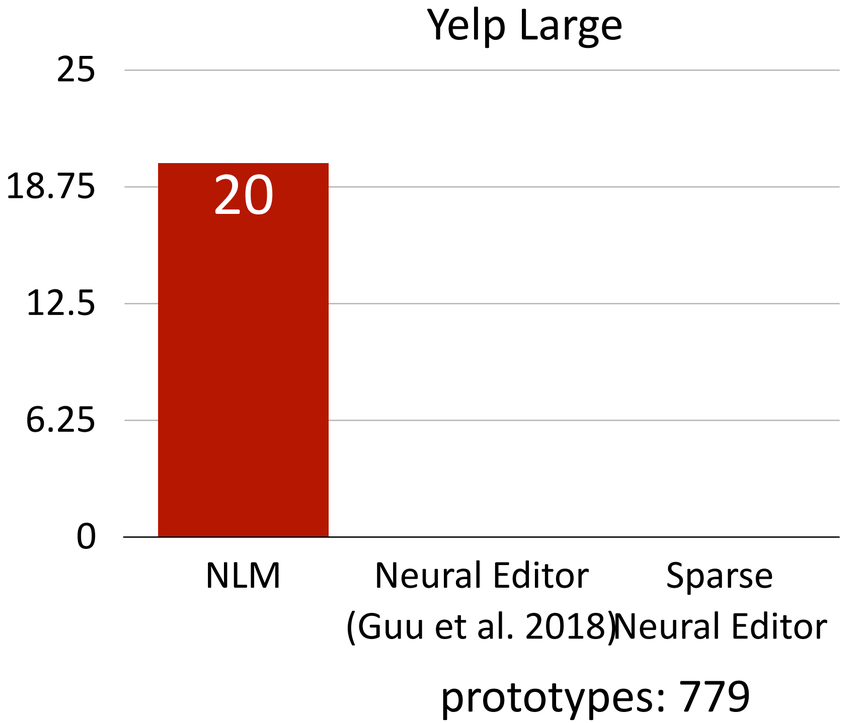

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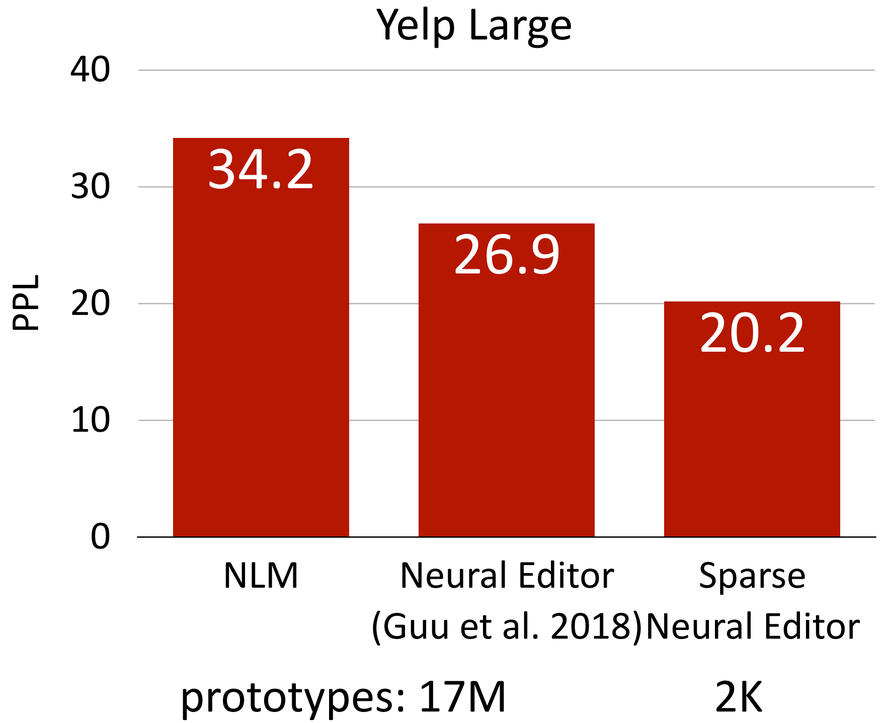

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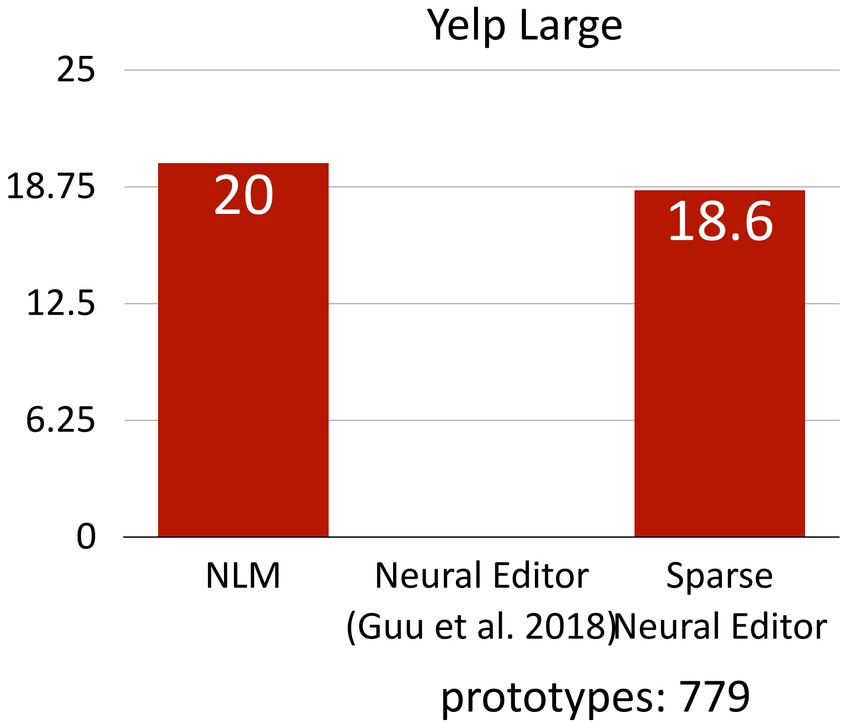
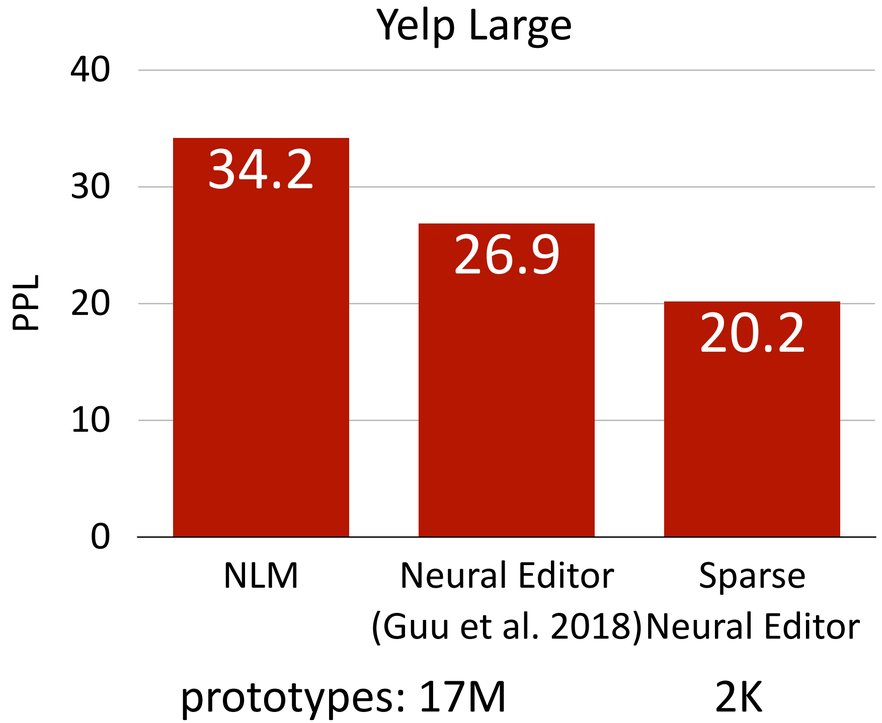
Perplexity Results



prototypes: 779

Yelp Medium

prototypes: 1.5k



prototypes: 17M

2K

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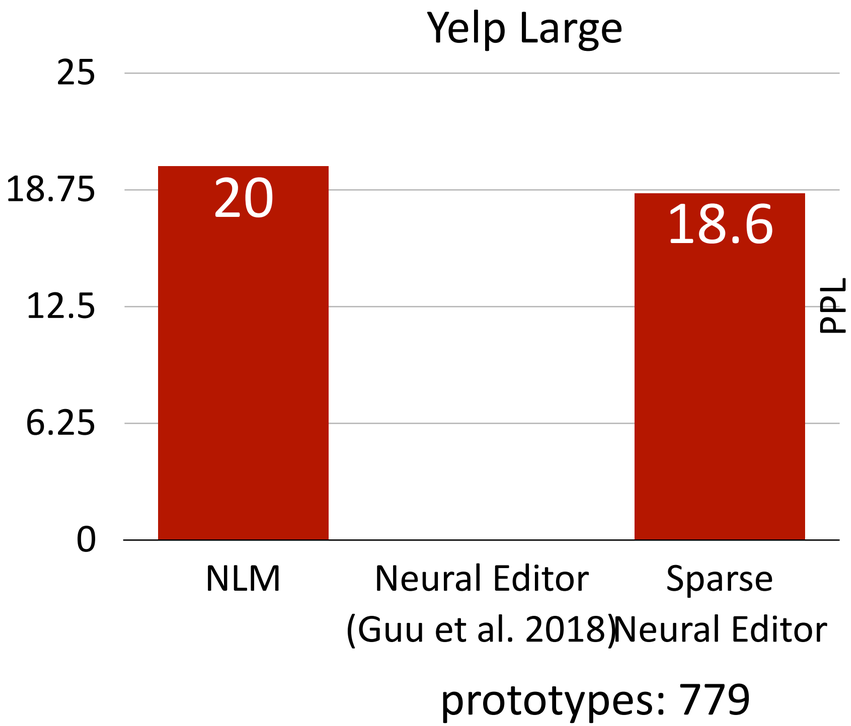

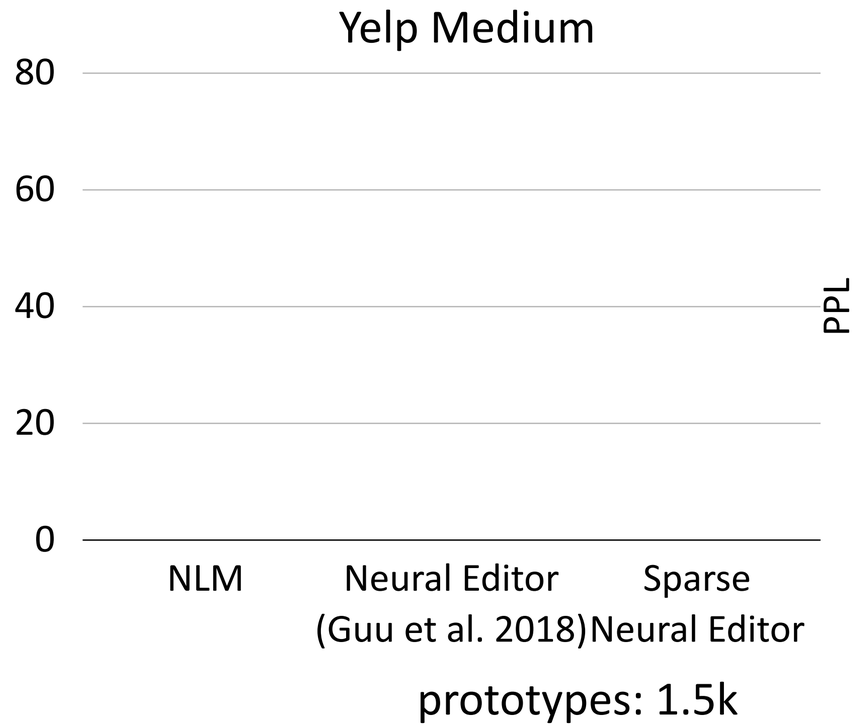

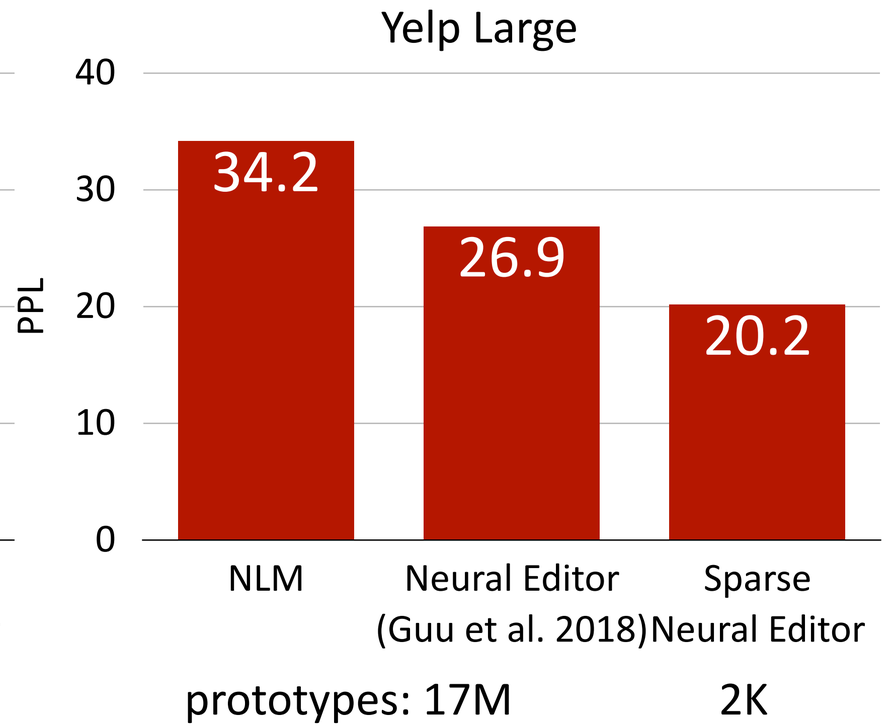

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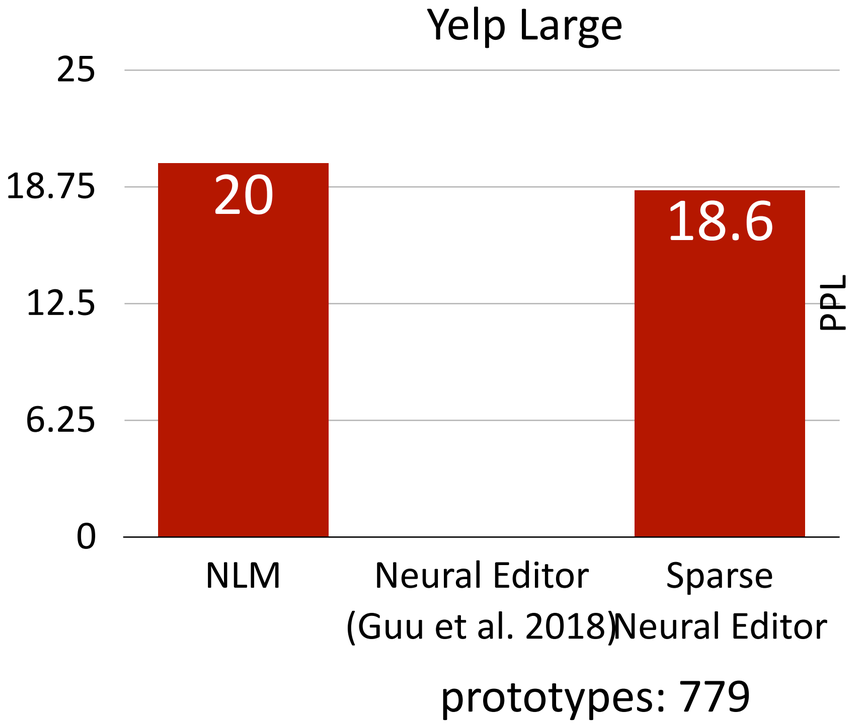

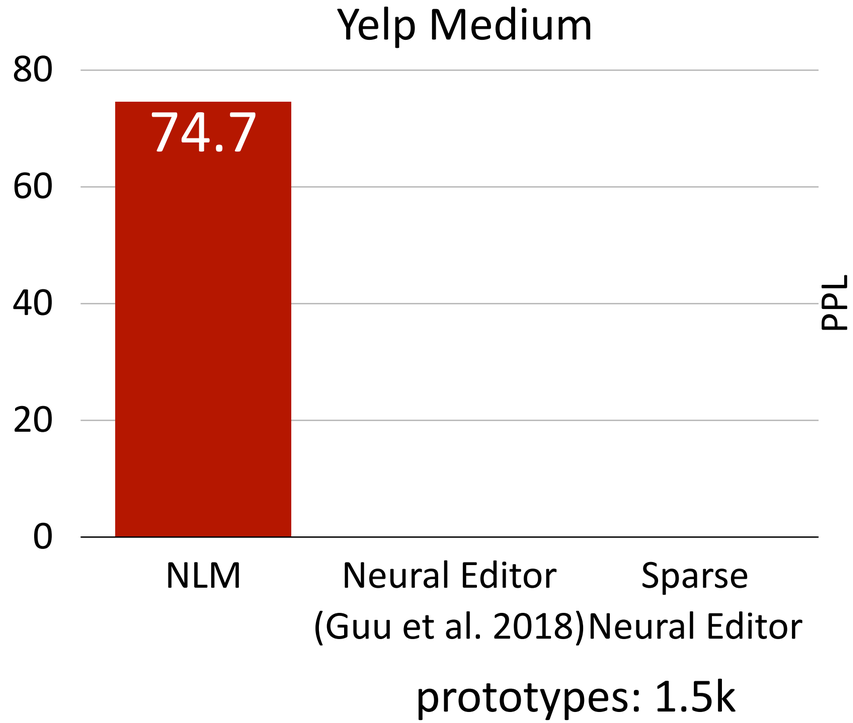

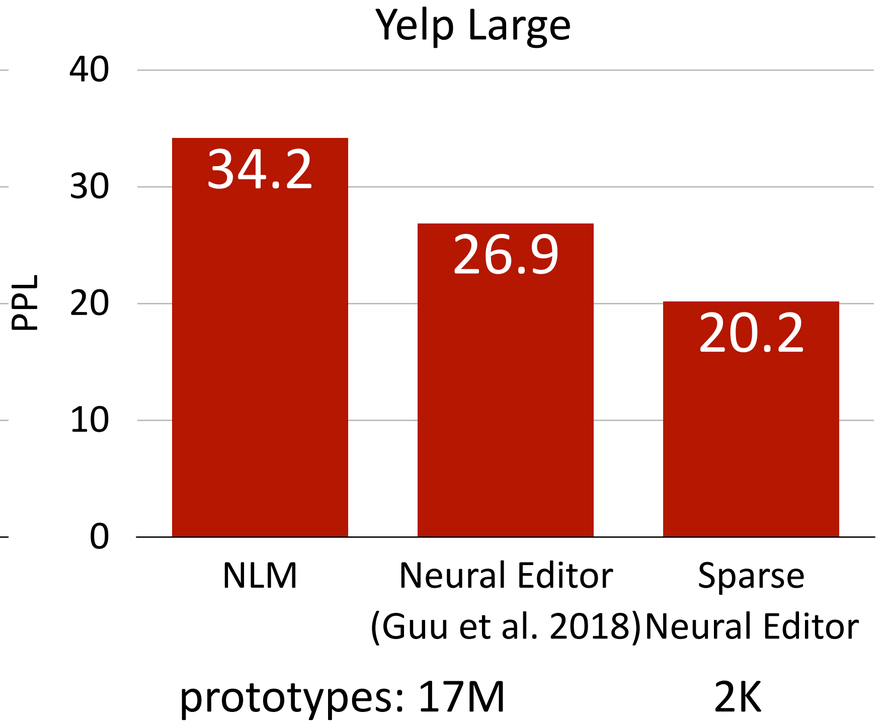

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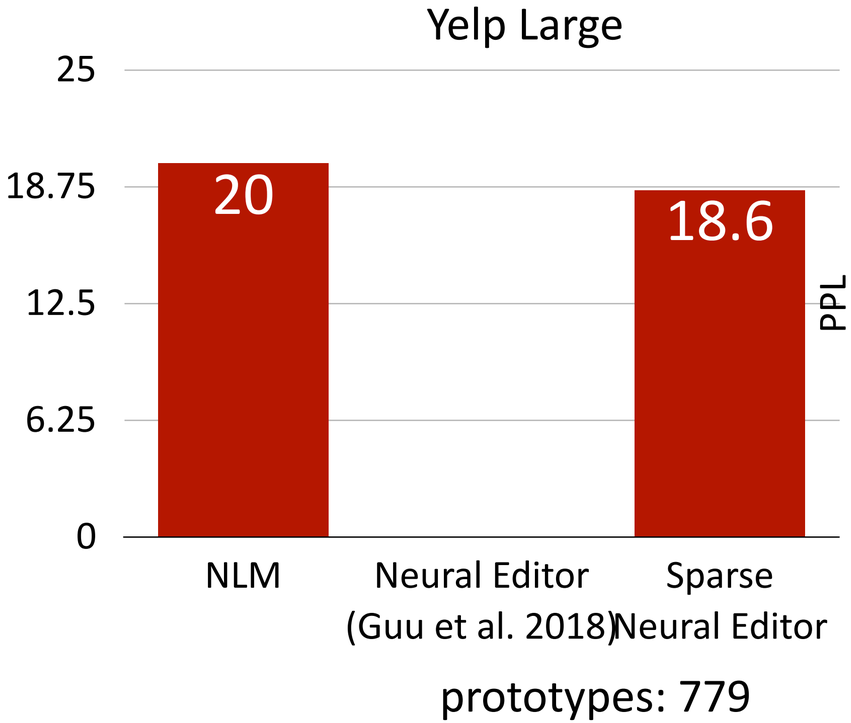
Perplexity Results



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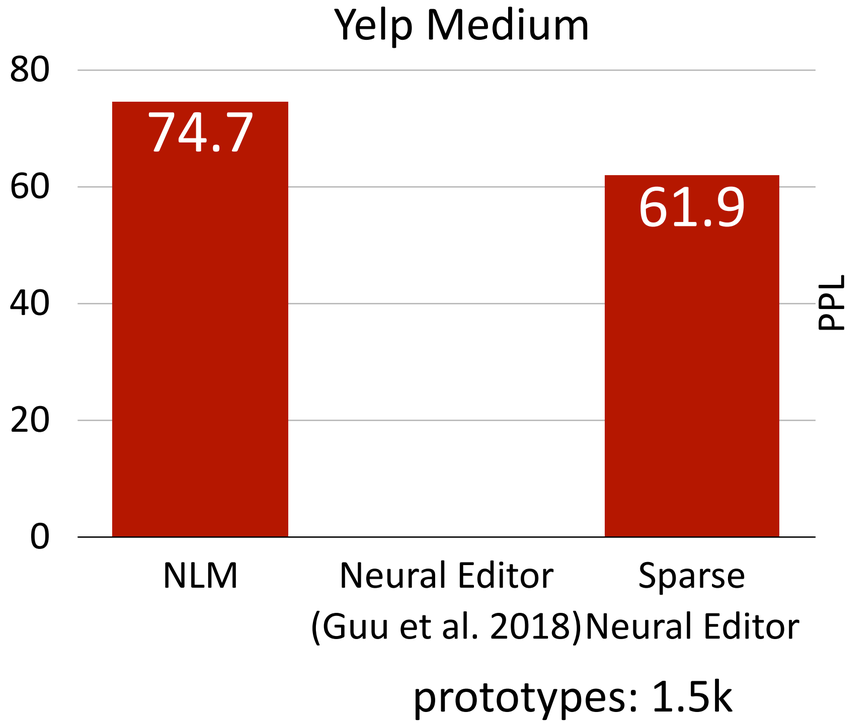

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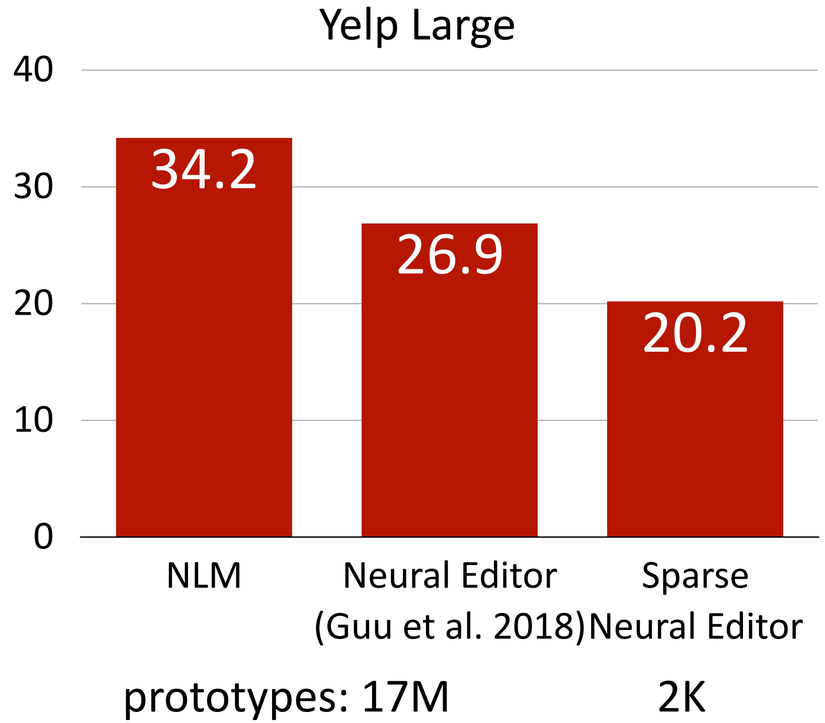

prototypes: 17M

2K

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Processing Speed Results

Yelp Large

prototypes: 17M 2K

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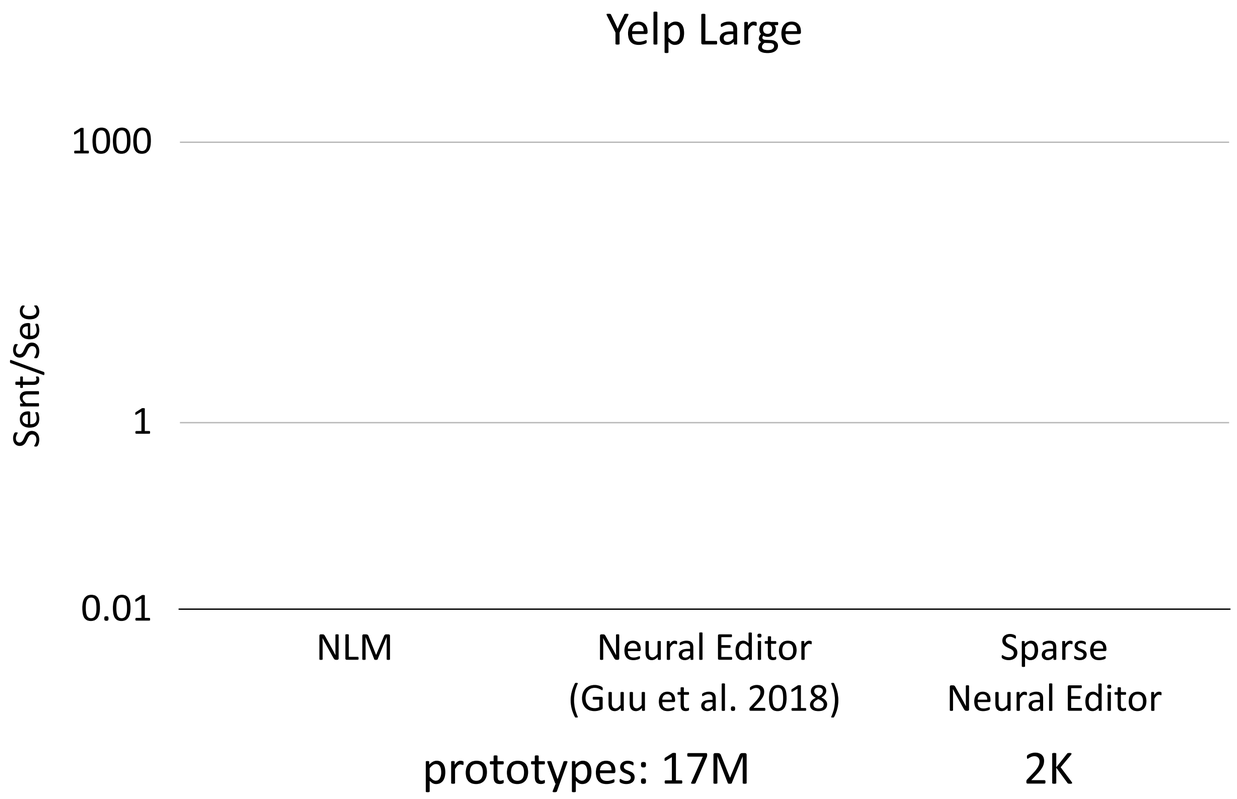
Processing Speed Results



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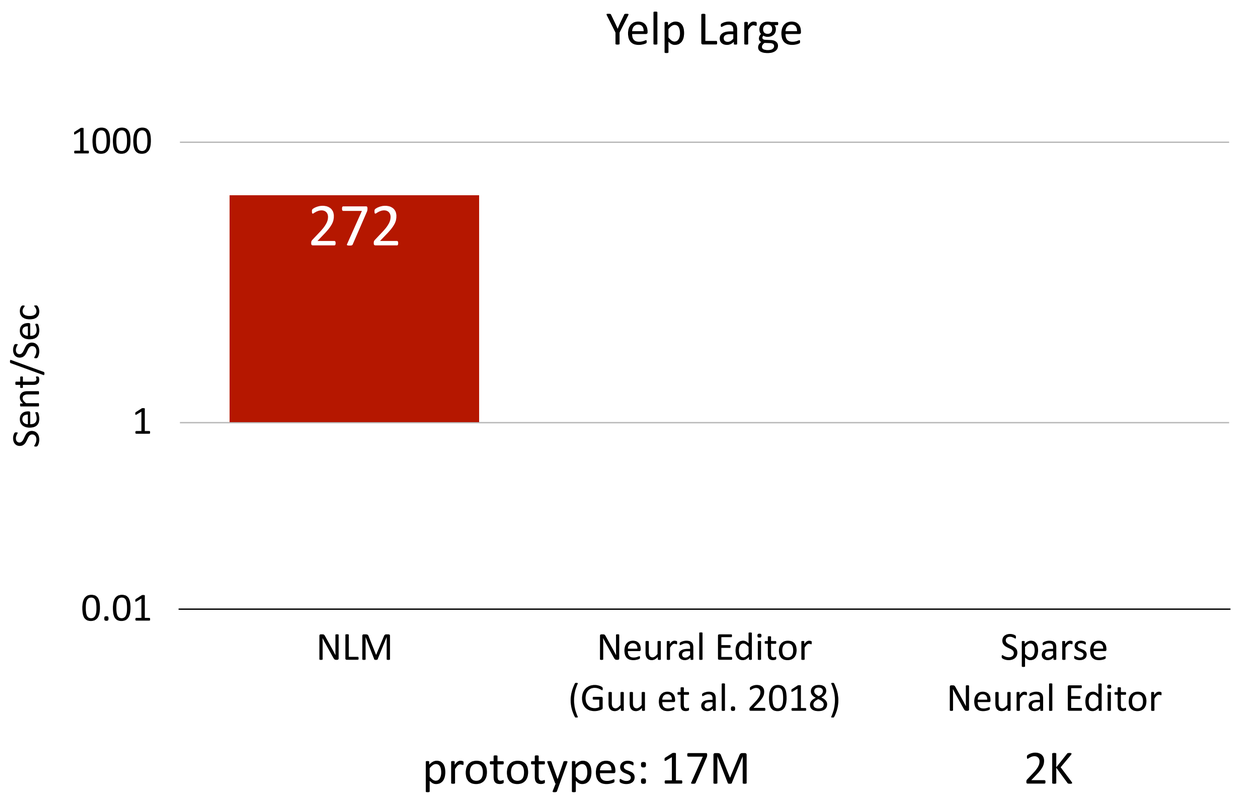
Processing Speed Results



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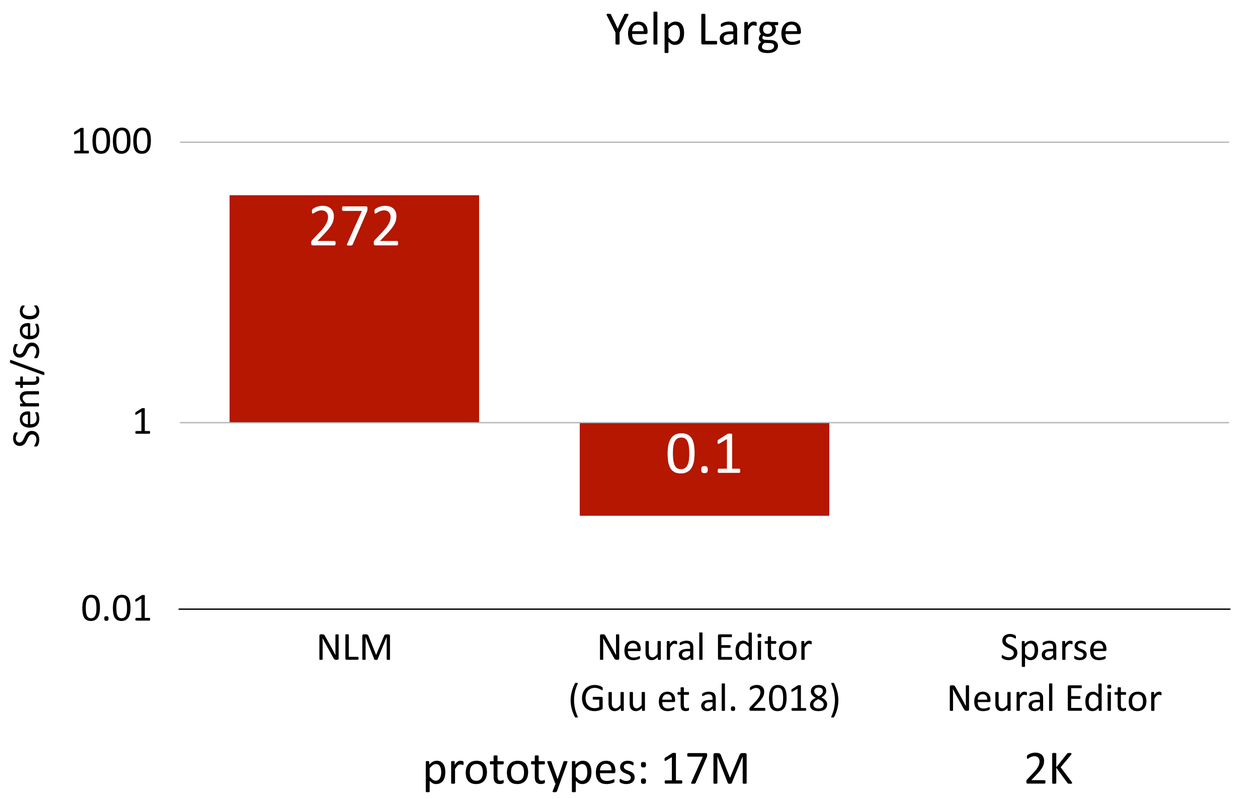
Processing Speed Results



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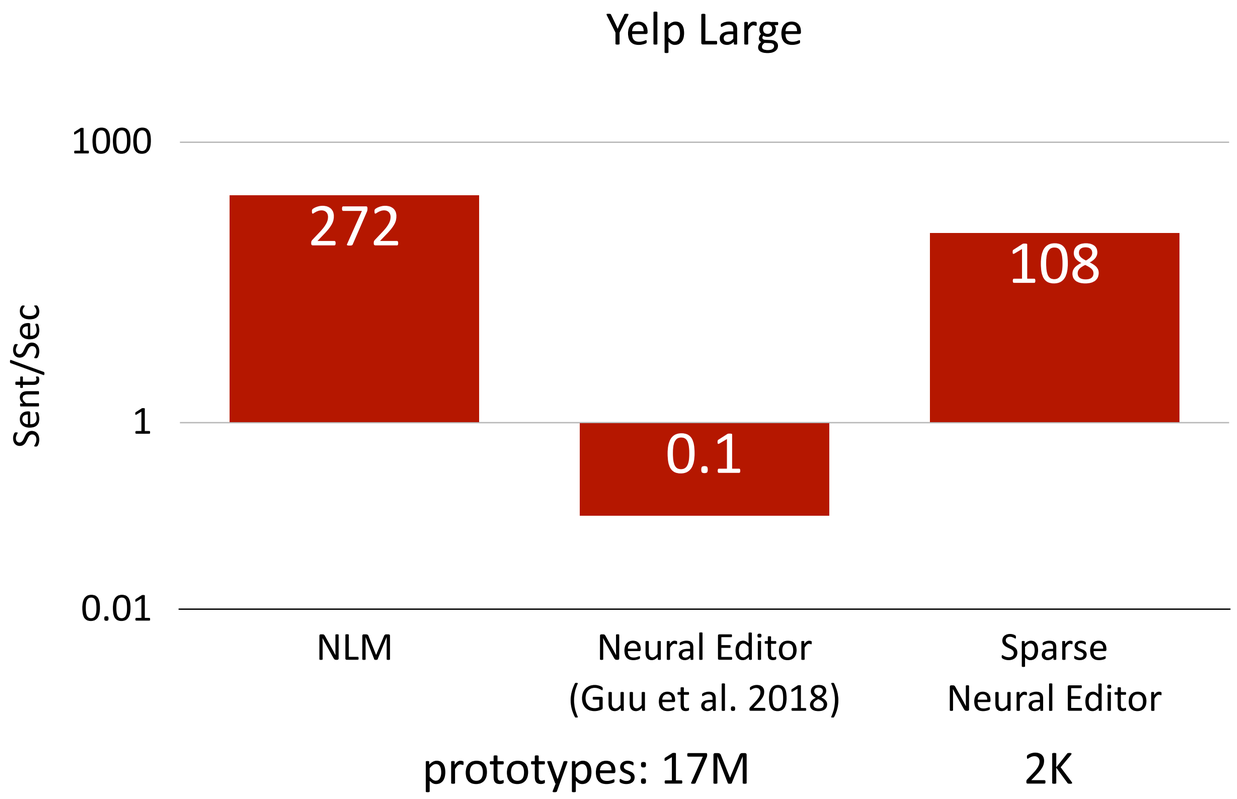
Processing Speed Results



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How Does Sparsity Affect Prototypes?

Dense prototypes see more semantic overlap, sparse prototypes are more syntactic.

Data Examples	Prototypes
the best corned beef hash i 've ever had !	(dense) the best real corned beef hash i 've had . (sparse) the chicken satay is the best i 've ever had .
the grilled chicken was flavorful , but too flavorful .	(dense) the chicken was moist but it lacked flavor . (sparse) my sandwich was good but the chicken was a little plain .
i asked her what time they close and she said <cardinal> o'clock .	(dense) i asked what time they closed <date> , and was told <cardinal> . (sparse) we asked how long the wait was and we were informed it would be <time> .

Table 2: Qualitative examples of prototypes when using denser and sparser prototype supports.

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How Does Sparsity Affect Prototypes?

Dense prototypes see more overlapping content words.

Model	Overall	NOUN	DET	AUX	PRON	ADJ	VERB
31K prototypes	91.2K	14.4K	9.6K	9.3K	9.0K	7.2K	6.4K
1.5K prototypes	74.7K	9.9K	8.5K	8.2K	7.3K	5.6K	4.4K
Relative Change	-18.1%	-31.3%	-11.5%	-11.8%	-18.9%	-22.2%	-31.3K

Table 1: Number of matching tokens between examples and their prototypes. Results are reported in cluster of POS tags.

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Example Generation Results

Prototype: A man is using a small laptop computer	Prototype: A cat sitting on a sidewalk behind a bush
A man is using his laptop computer with his hands on the keyboard	A cat laying on top of a wooden bench
A man is using a laptop computer with his hands on the keyboard	A cat standing next to a tree in a park
A man is using a laptop computer while sitting on a bench	Two cats sitting on a bench near a park bench
A man is using a laptop computer in the middle of a room	A dog sitting on a bench near a park bench
A young man is using a laptop computer in the middle of a room	A dog sitting on a bench near a park bench

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Conclusion

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Summary

- Prototype support can be sparse to improve efficiency — superior over previous neural editor model with only 1‰ of datastore and 1‰ of test time
- Prototypes tend to drop semantic but keep syntactic information when they grow sparser

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Future Directions?

- **MANY** other promising non-parametric models! How do they play with sparsity?
- What is the interaction between big non-parametric models and small parametric models? Do we need 100 billion parameters if we have Google search?

Code available, try it out!

https://github.com/jxhe/sparse-text-prototype