

Neuro-Symbolic Language Modeling with Automaton-augmented Retrieval

Appeared in ICML'2022

Uri Alon, Frank F. Xu, Junxian He, Sudipta Sengupta, Dan Roth, Graham Neubig

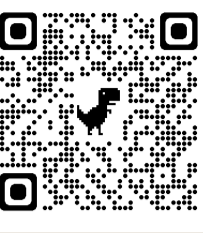
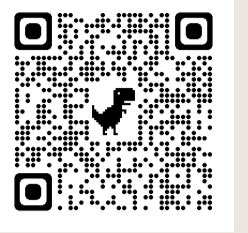


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Language Technologies Institute



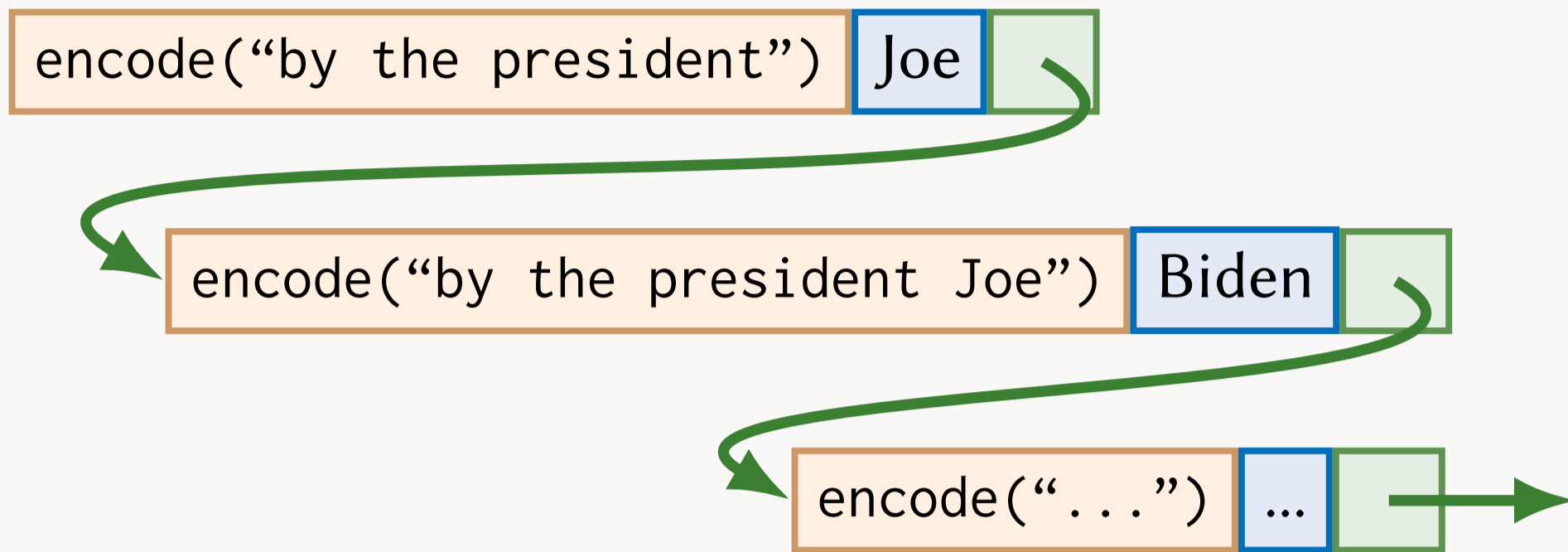
<https://github.com/neulab/retomaton>

<https://github.com/neulab/knn-transformers>



Key Idea #1: Pointers Between Examples

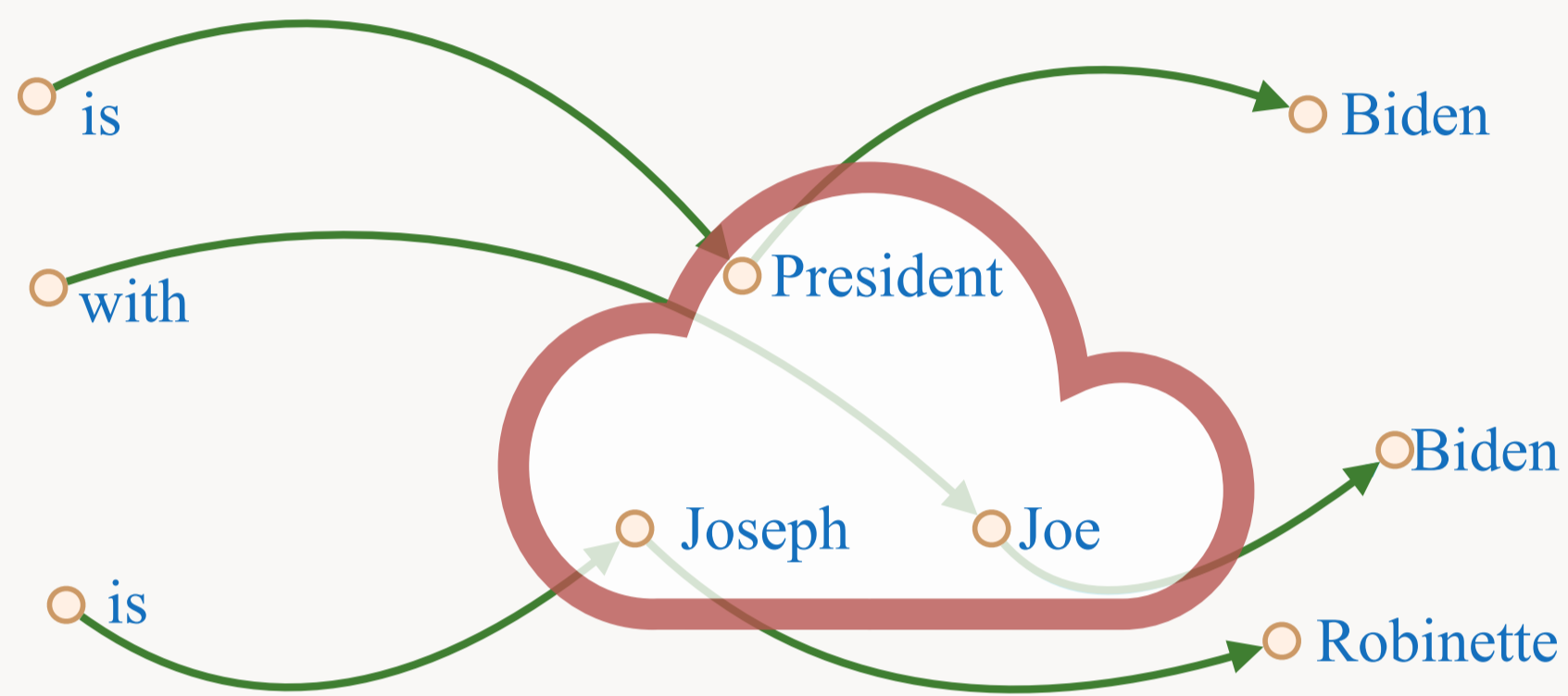
Encode the training set as linked lists of $(key, value, pointer)$:



This extends k NN-LM (Khandelwal et al., '2020) by adding *pointers* between consecutive datastore entries.

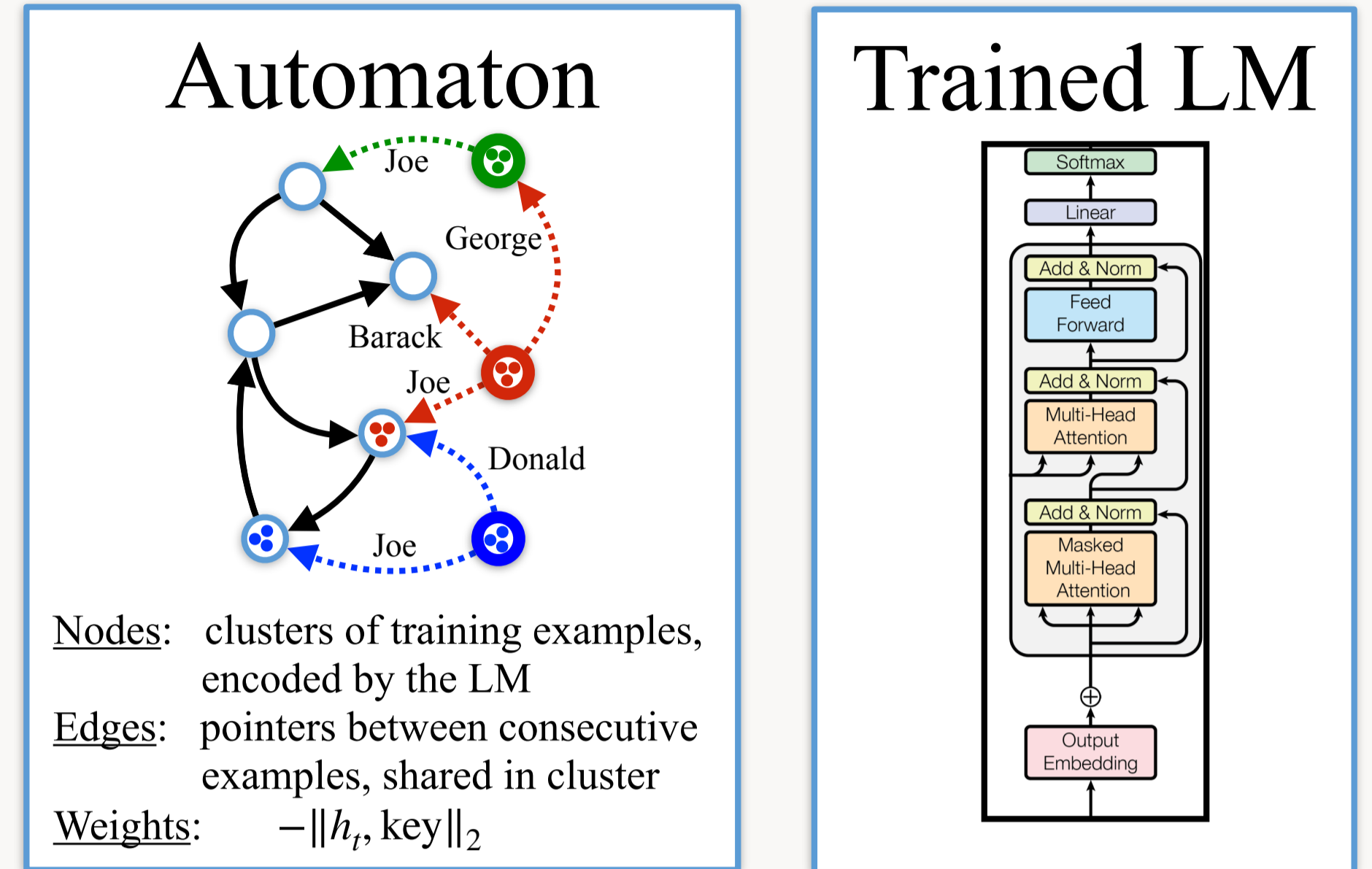
Key Idea #2: Clustering Similar Keys

Cluster similar keys into automaton states:



RETOMATON

Test context: The president is _____



Nodes: clusters of training examples, encoded by the LM

Edges: pointers between consecutive examples, shared in cluster

Weights: $-||h_t, key||_2$

$$\lambda P_{auto} + (1 - \lambda) P_{LM}$$

$$P_{auto}(w | h_t, states_t) \propto \sum_{s \in states_t} \sum_{(key, val) \in s, val=w} \exp(-||h_t, key||_2)$$

Results

In-domain Datastore

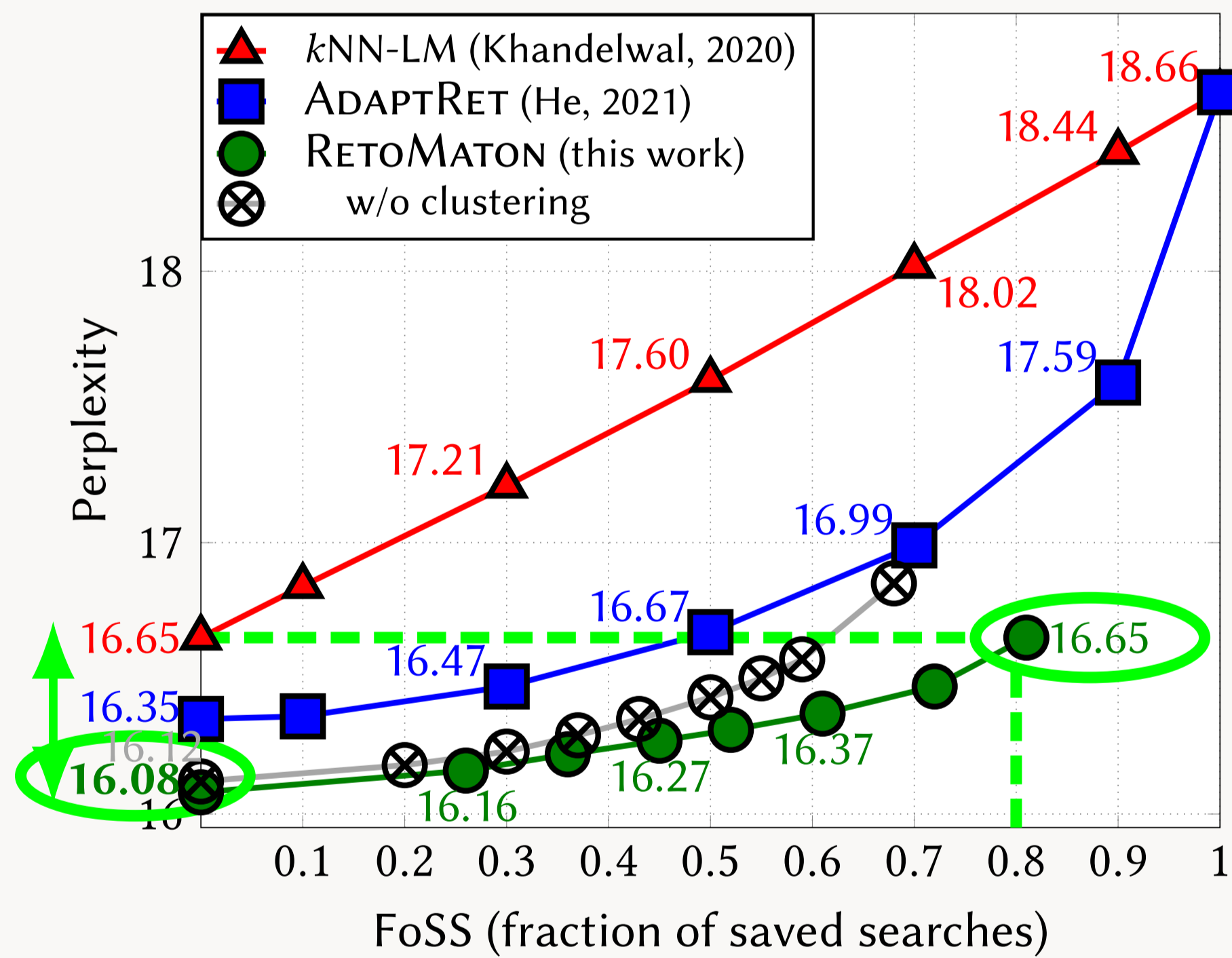


Figure: Experiments on WIKITEXT-103, where the datastore is created from the same training set that the base LM was trained on.

Domain Adaptation

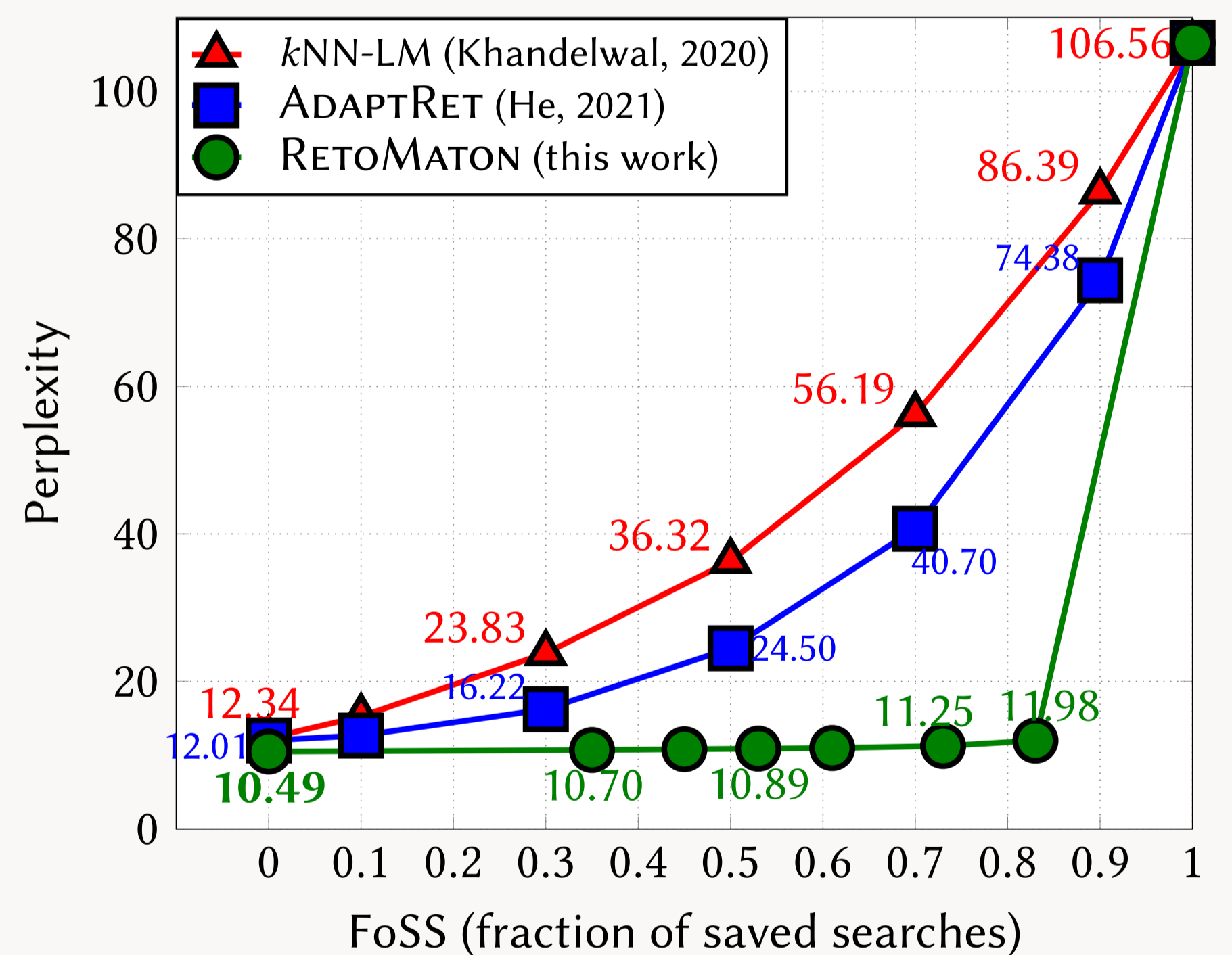


Figure: Domain adaptation experiments: the model was trained on News Crawl, and the datastore is constructed from Law-MT.

Improving Fine-tuning

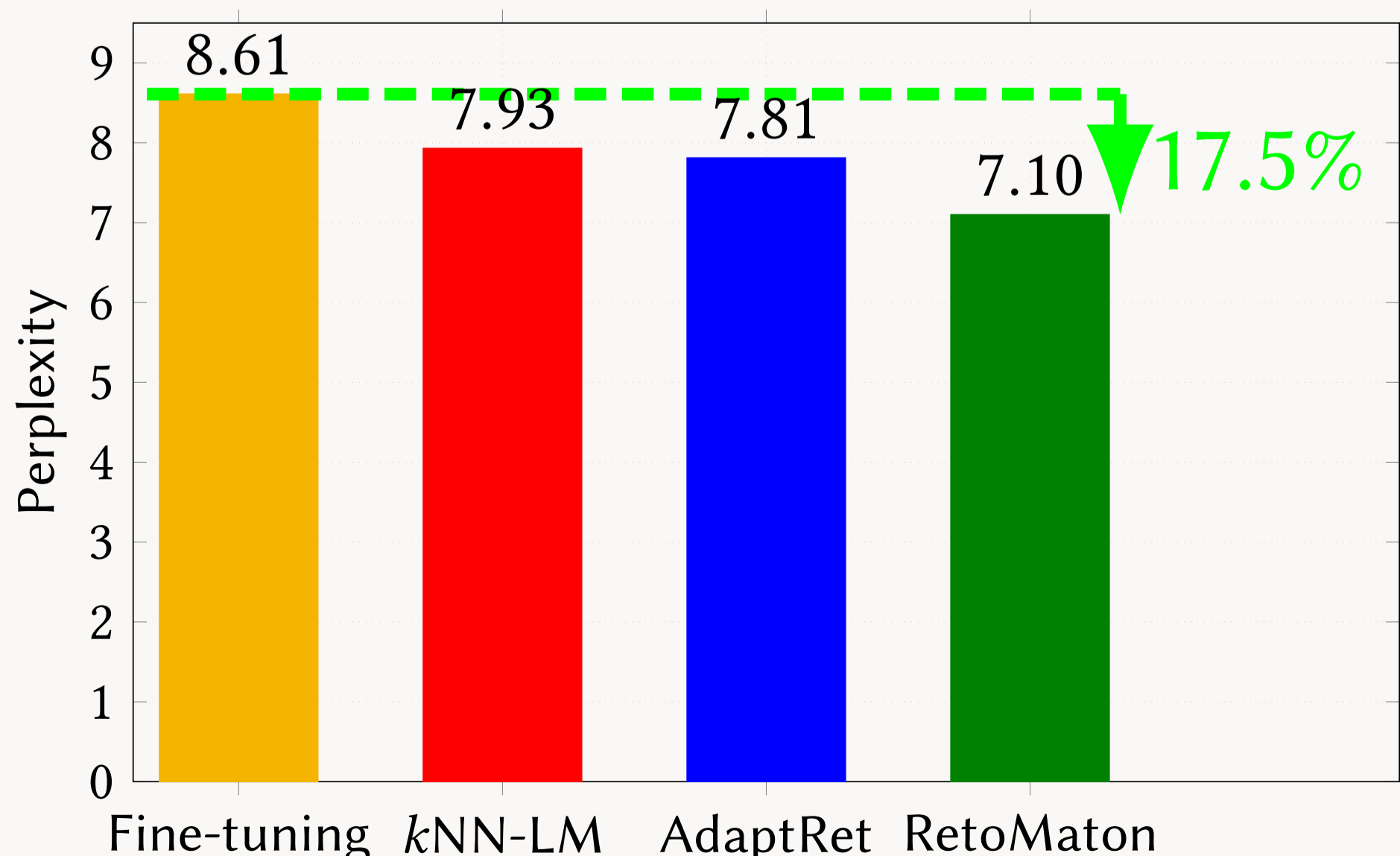


Figure: When constructing RETOMATON on top of a fine-tuned model, RETOMATON reduces perplexity by 17.5%.

Sample

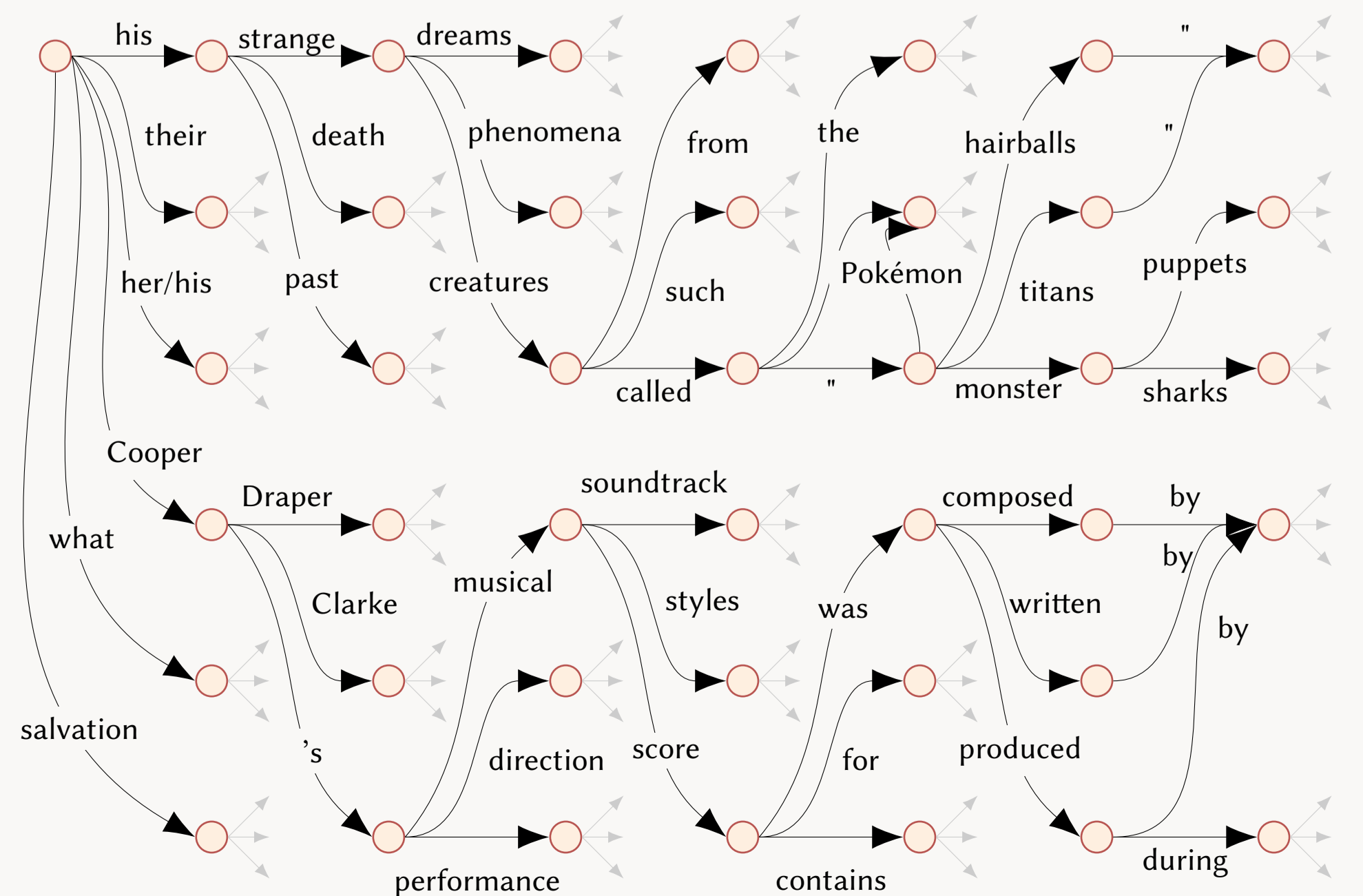


Figure: A sample of the automaton constructed from WIKITEXT-103