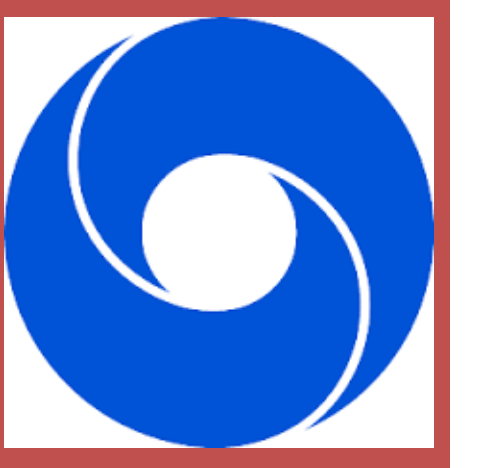




End-to-End Training of Multi-Document Reader and Retriever for Open-Domain Question Answering

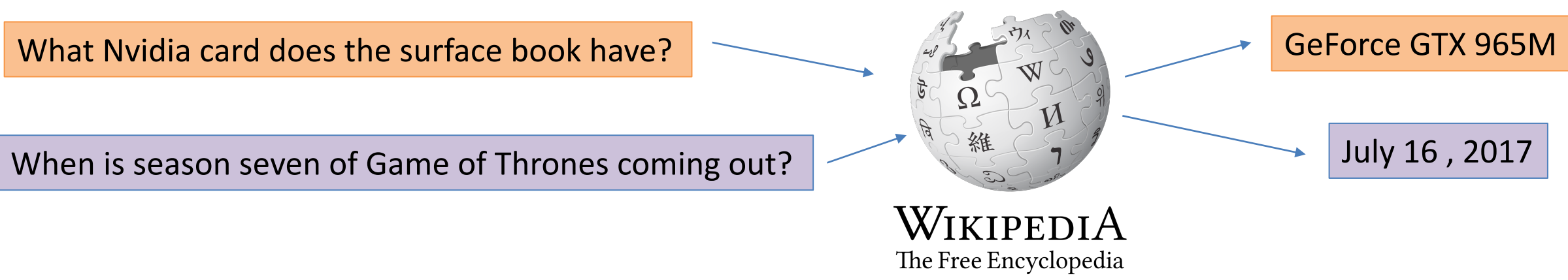


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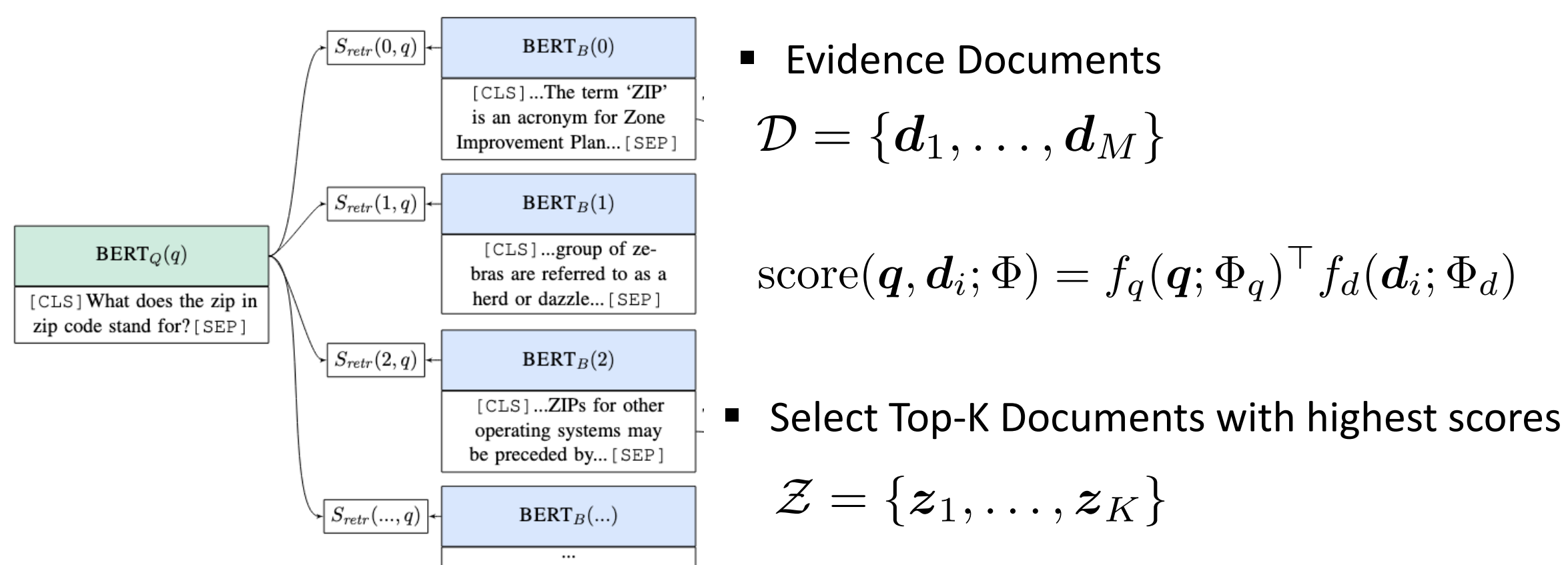
Introduction

Open-Domain Question Answering

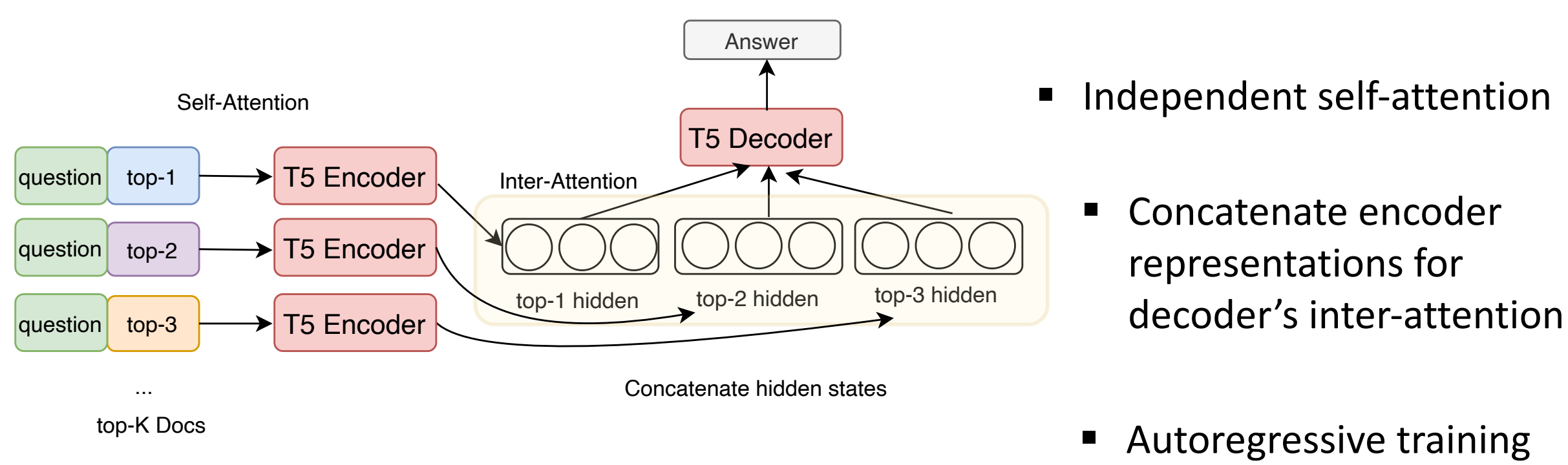


- Input: Question (q) and evidence documents (D) such as Wikipedia
- Output: Answer (a)

Retriever: Dual Encoder



Multi-Document Reader: Fusion-in-Decoder (FiD)



Research Question

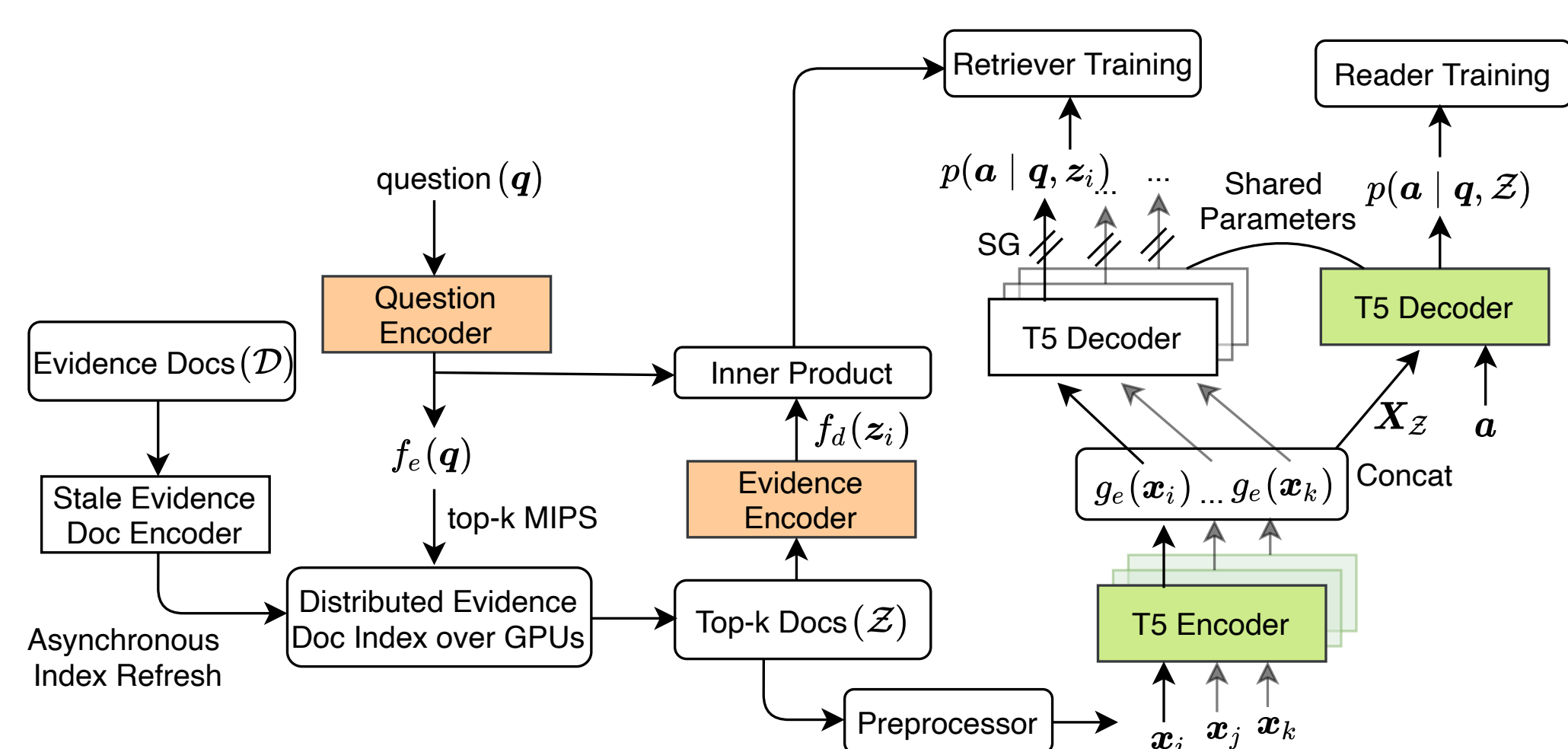
How to jointly train the FiD reader and dual-encoder retriever?

Methods

EMDR²: Training Objective

$$\mathcal{L} = \underbrace{\log p(\mathbf{a} | \mathbf{q}, \mathcal{Z}_{\text{top-}K}; \Theta)}_{\text{reader}} + \underbrace{\log \sum_{k=1}^K \text{SG}(p(\mathbf{a} | \mathbf{q}, \mathbf{z}_k; \Theta)) p(\mathbf{z}_k | \mathbf{q}, \mathcal{Z}_{\text{top-}K}; \Phi)}_{\text{retriever}}$$

Training Pipeline



EMDR²: Expectation-Maximization View

Algorithm 1: End-to-end training of multi-document reader and retriever.

Input: Model parameters Θ and Φ , evidence documents \mathcal{D} .

```

while not converged do
  • Compute  $\mathcal{Z}_{\text{top-}K}$  using the current retriever parameters  $\Phi$ . // E-step
  • Compute  $p(\mathbf{a} | \mathbf{q}, \mathbf{z}_k)$  for each  $\mathbf{z}_k$  using the current reader parameters  $\Theta$ . // E-step
  • Update model parameters  $\Theta$  and  $\Phi$  to maximize the log-likelihood in Eq. 6. // M-step
end

```

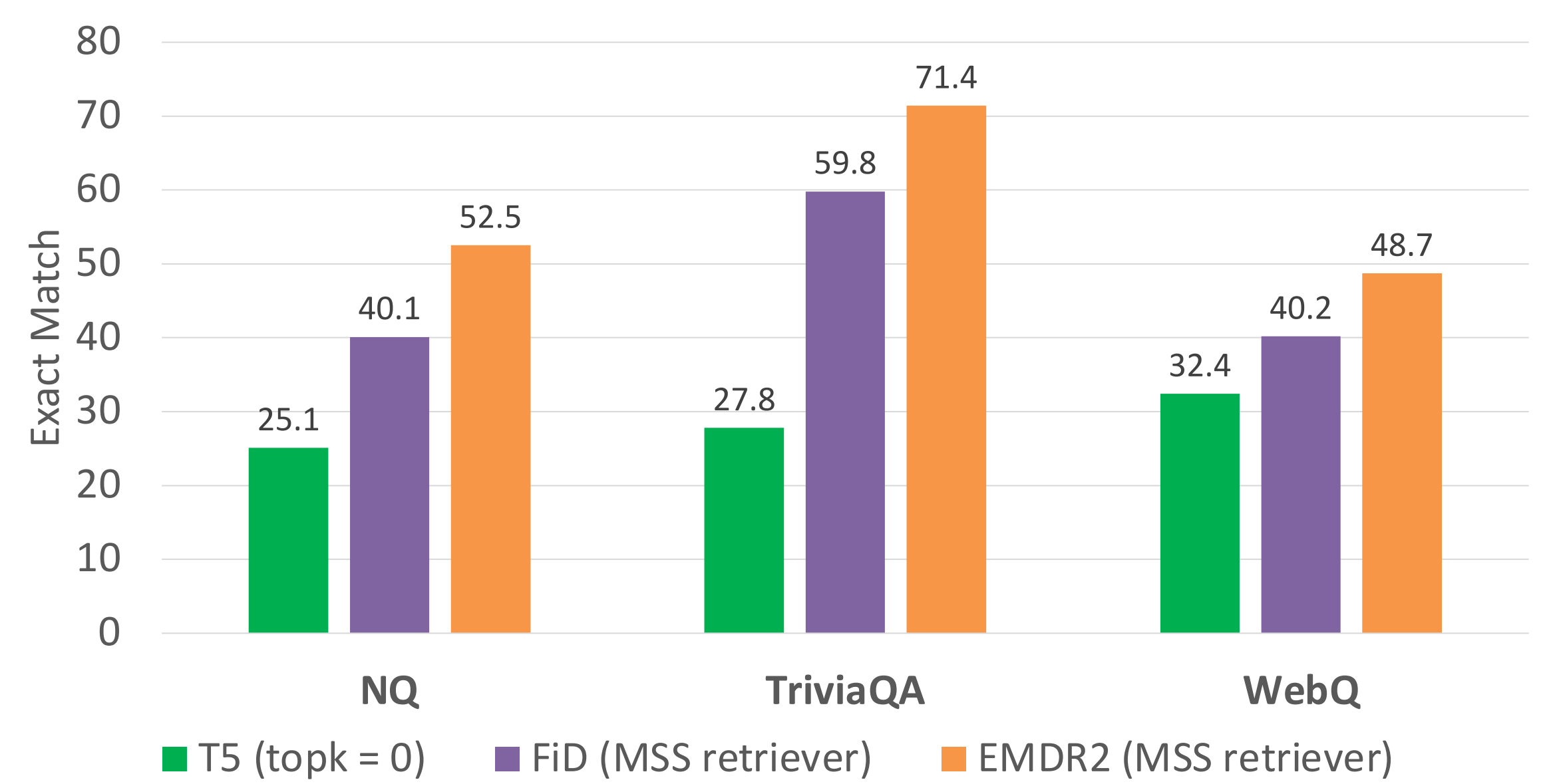
Comparison with Recent Methods

Methods	Multi-Doc Reader	Retriever Adaptation	End-to-End Training	Unsupervised Retriever
REALM		✓	✓	✓
DPR				
RAG		✓	✓	
FiD	✓			
FiD-KD	✓	✓		
EMDR²	✓	✓	✓	✓

Results and Analysis

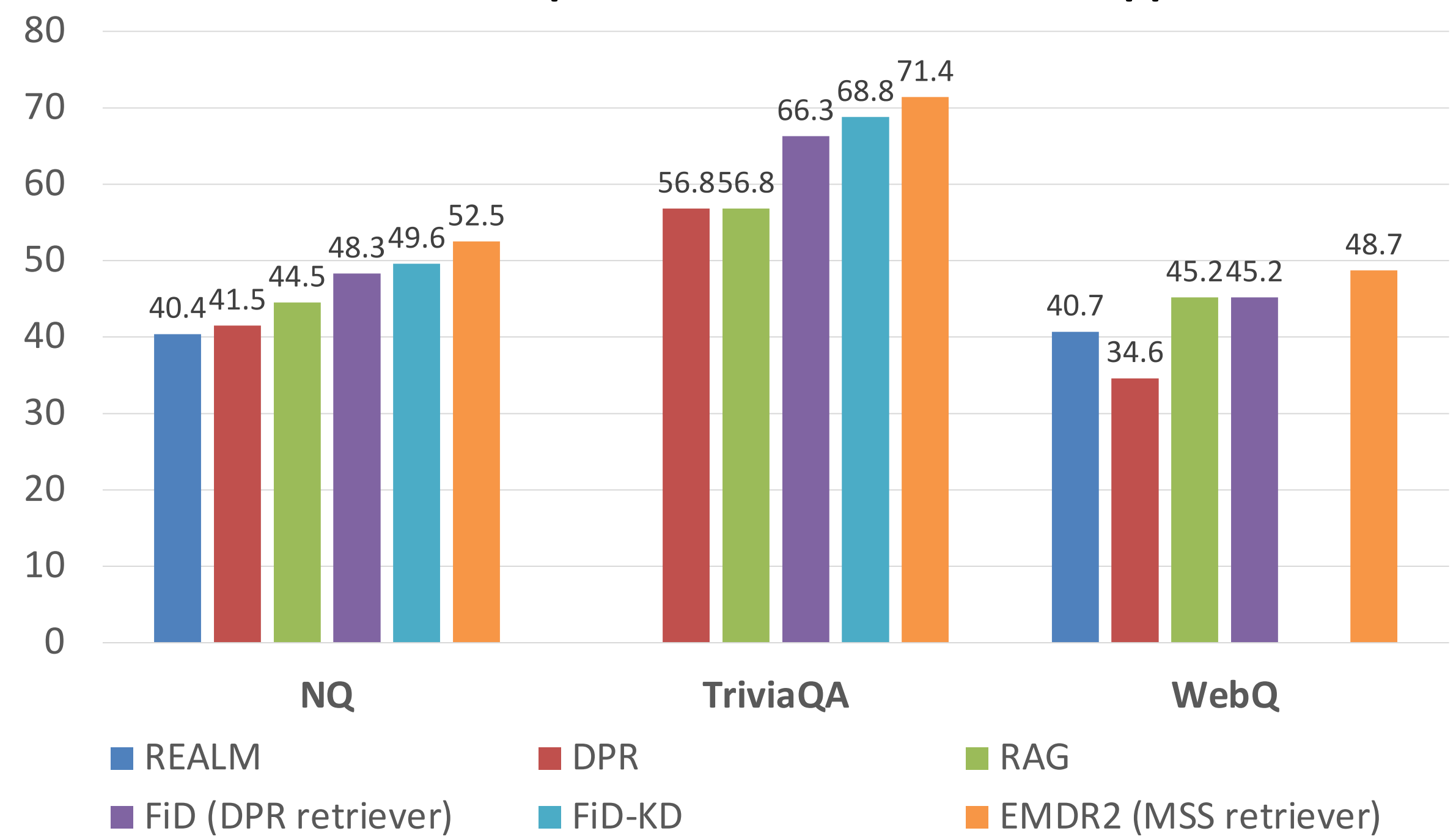
- Bootstrap the model with unsupervised masked salient spans (MSS) training.

Supervised EMDR² Training



- 8-12 EM points gain over no end-to-end training.

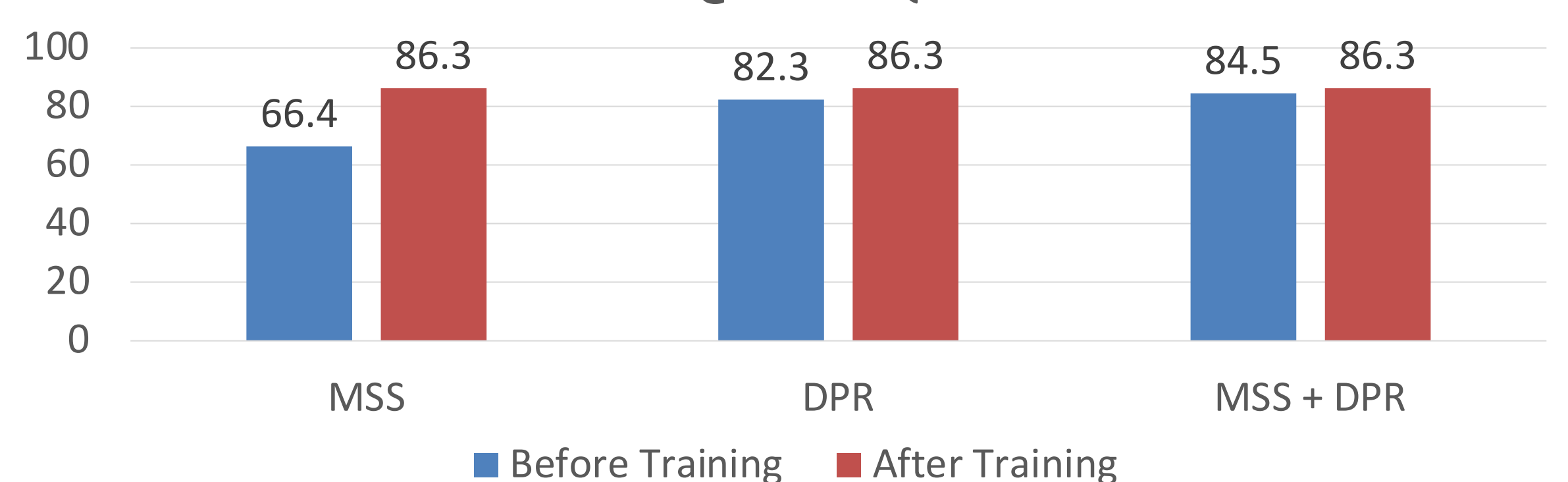
Performance Comparison with Other Recent Approaches



- 2-3 EM points gain over previous SOTA results.

Effect of Retriever Initialization

Recall @ 50 on NQ Dev



- Different retriever initializations converge to the same final recall.
- Additional retriever training by DPR shows no further performance gains.

Conclusions

- We obtain *state-of-the-art results* with a new end-to-end training algorithm.
- Requires *single training cycle* of retriever and reader training.
- Supervised retriever* initialization may not be necessary for SOTA performance.