Copy That! Editing Sequences by Copying Spans

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Intelligent Editors

Bug Fixing

```
public Integer getMinElement(List myList) {
    if(myList.size() >= 0) {
        return ListManager.getFirst(myList);
    }
    return 0;
}
```

→

```
public Integer getMinElement(List myList) {
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    return null;
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```

(Tufano et al., 2019)

Code Refactoring

`foo(x =>{return 4;})` → `foo(x=>4)` *(Yin et al., 2019)*

Grammatical Error Correction

Neither of the two traffic lights are working → Neither of the two traffic lights is working *(Park et al., 2020)*

Style Transfer

Gotta see both sides of the story. → You have to consider both sides of the story. *(Rao and Tetreault, 2018)*

Text Simplification

He came back home and played piano. → He came back home. He played piano. *(Sulem et al., 2018)*

Learning to edit sequences

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Learning to edit sequences by copying spans

Seq2Seq Generation

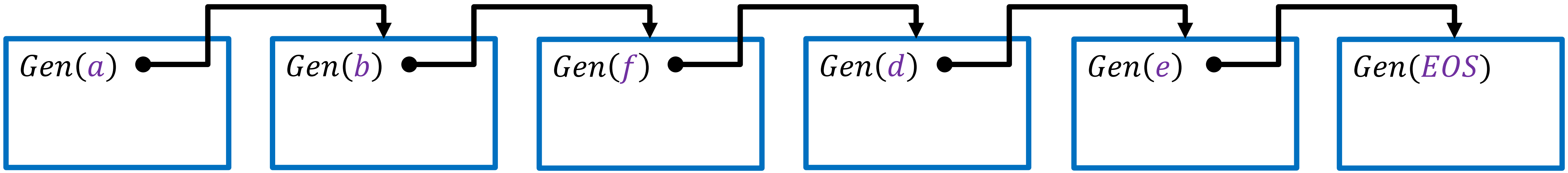
$\boldsymbol{in}$: input sequence
$\boldsymbol{out}$: output sequence ($o_0 \ldots o_m$)

$$p(o_0 \ldots o_m \mid \boldsymbol{in}) = \prod_{0 \le k \le m} p(o_k \mid \boldsymbol{in}, o_0 ... o_{k-1})$$

$$p(o_k \mid \boldsymbol{in}, o_0 ... o_{k-1}) = Gen(o_k)$$

Probability for generating o_k from vocabulary

a b c d e → a b f d e



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Probability for generating o_k from vocabulary
OR copying o_j from $\textbf{in}[pos]$
Pointer Networks (Vinyals et al., 2015)

$$= \sum_{\alpha \in A_k} q(\alpha \mid \textbf{in}, o_0 \ldots o_{k-1})$$

Sum of all correct actions $\alpha \in A_k$ when decoding k^{th} token
Kinds of actions (α):

- Gen(token)
- $Copy$(token, pos)

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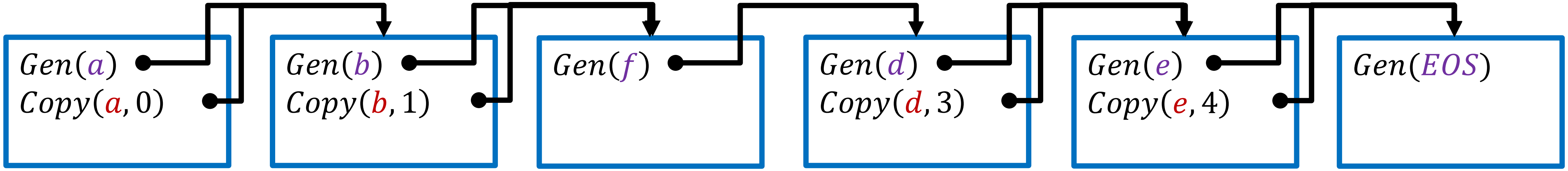

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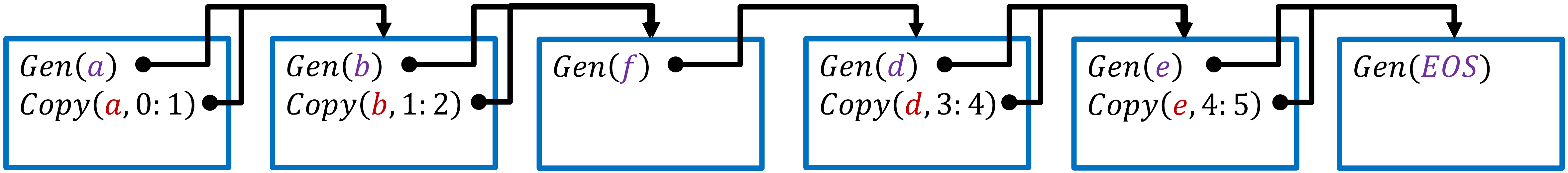

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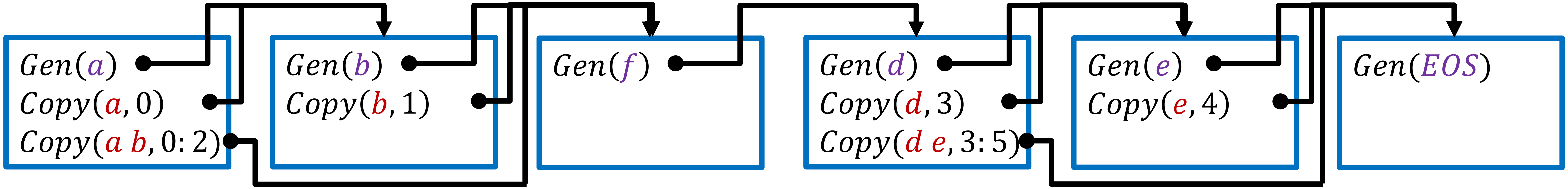
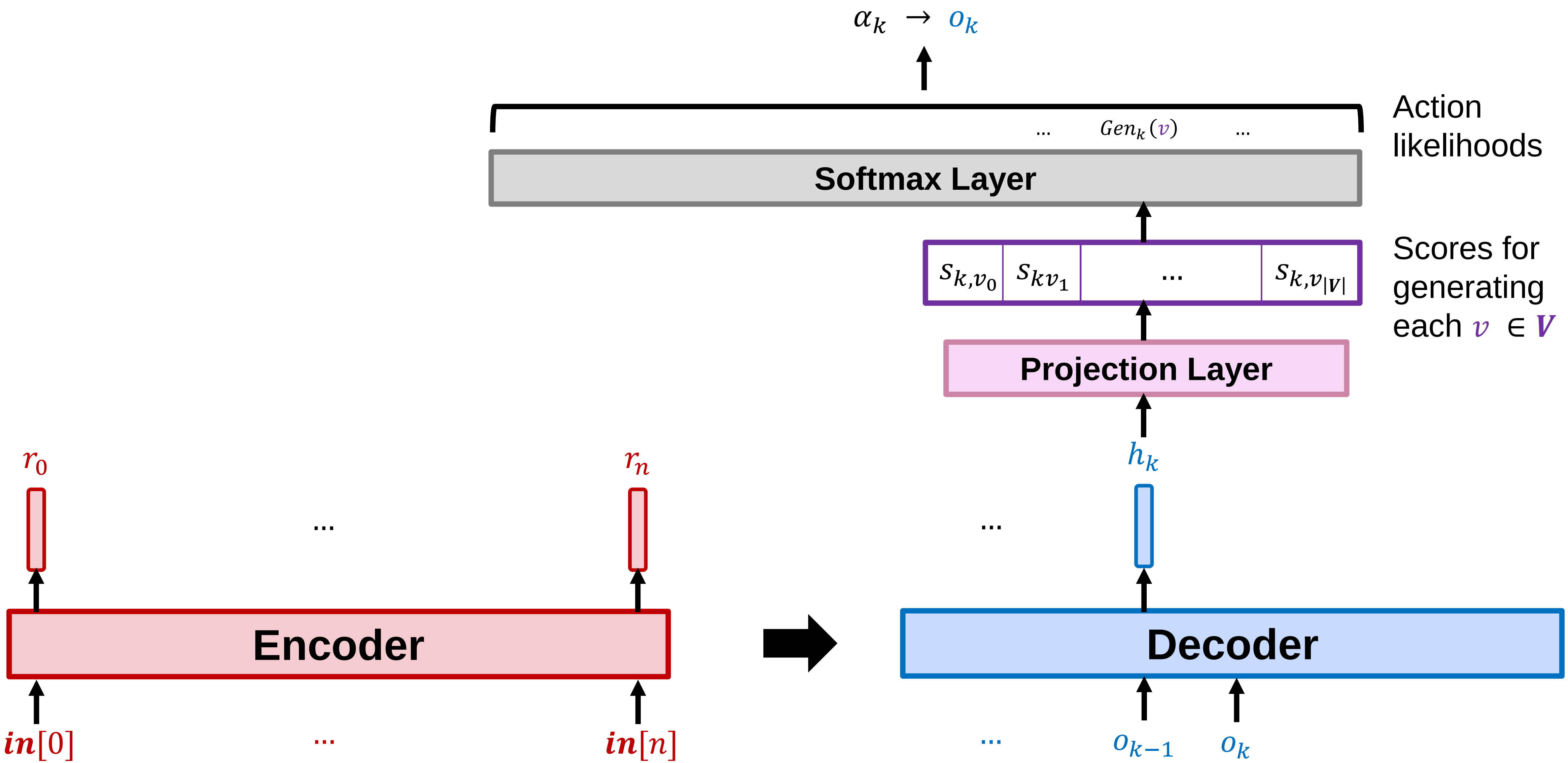


Seq2Seq + Span Copying



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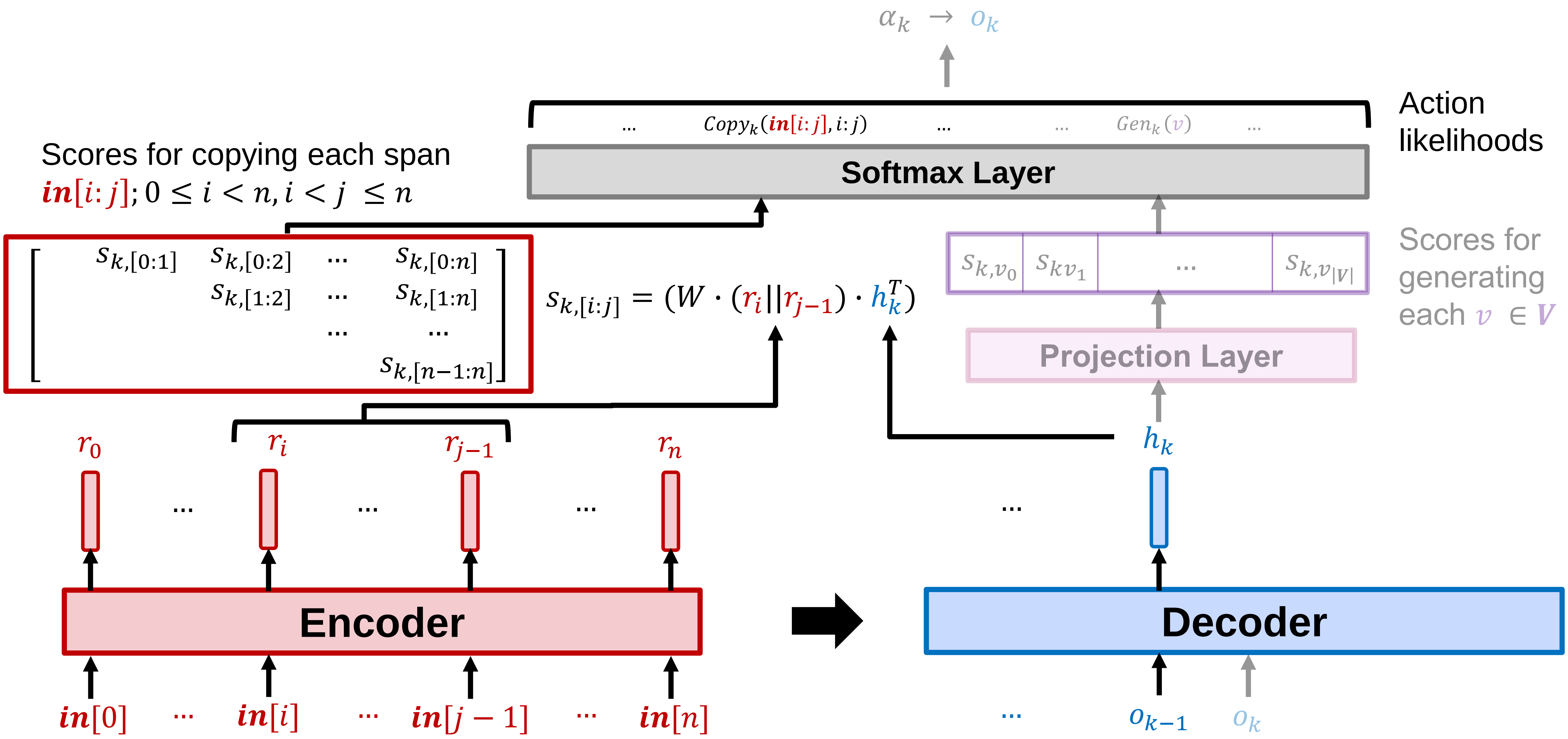

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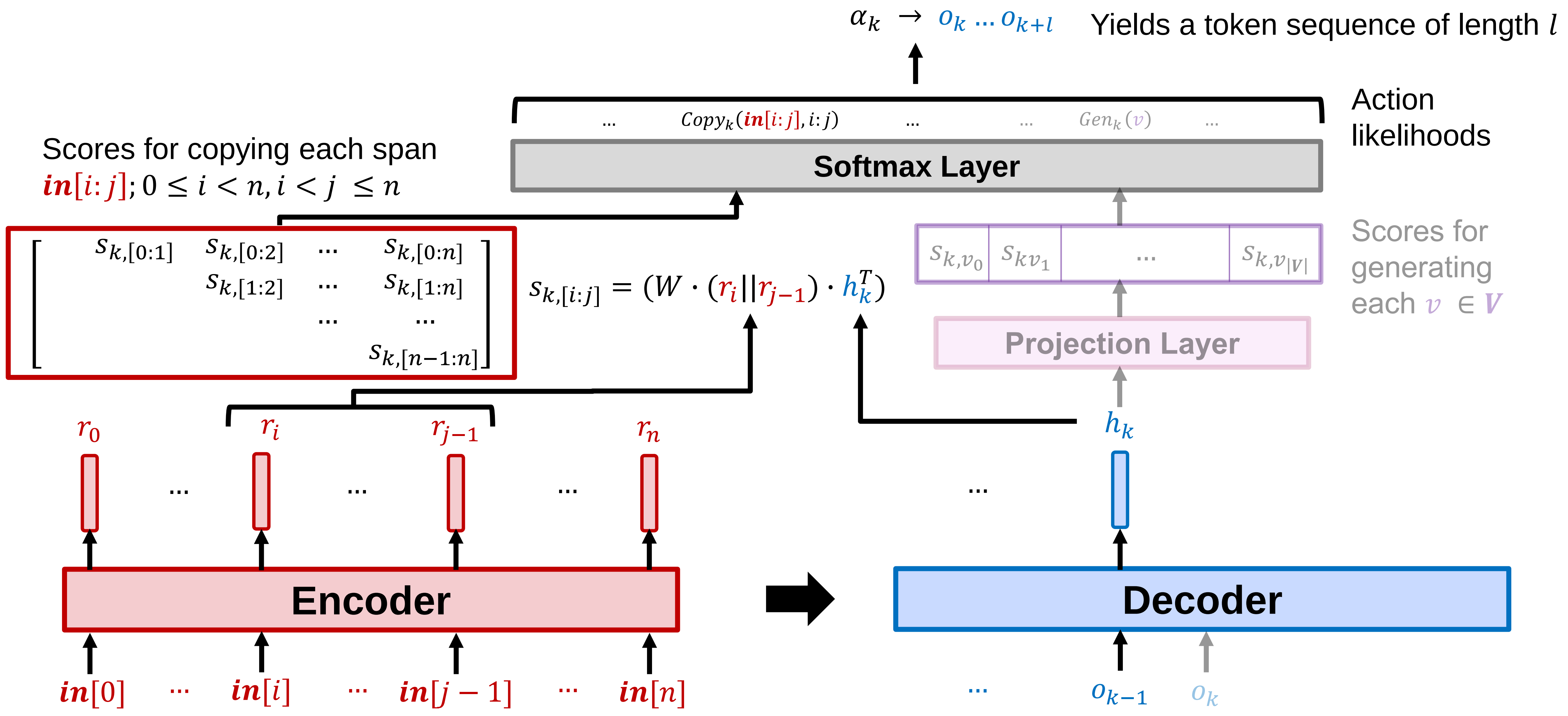

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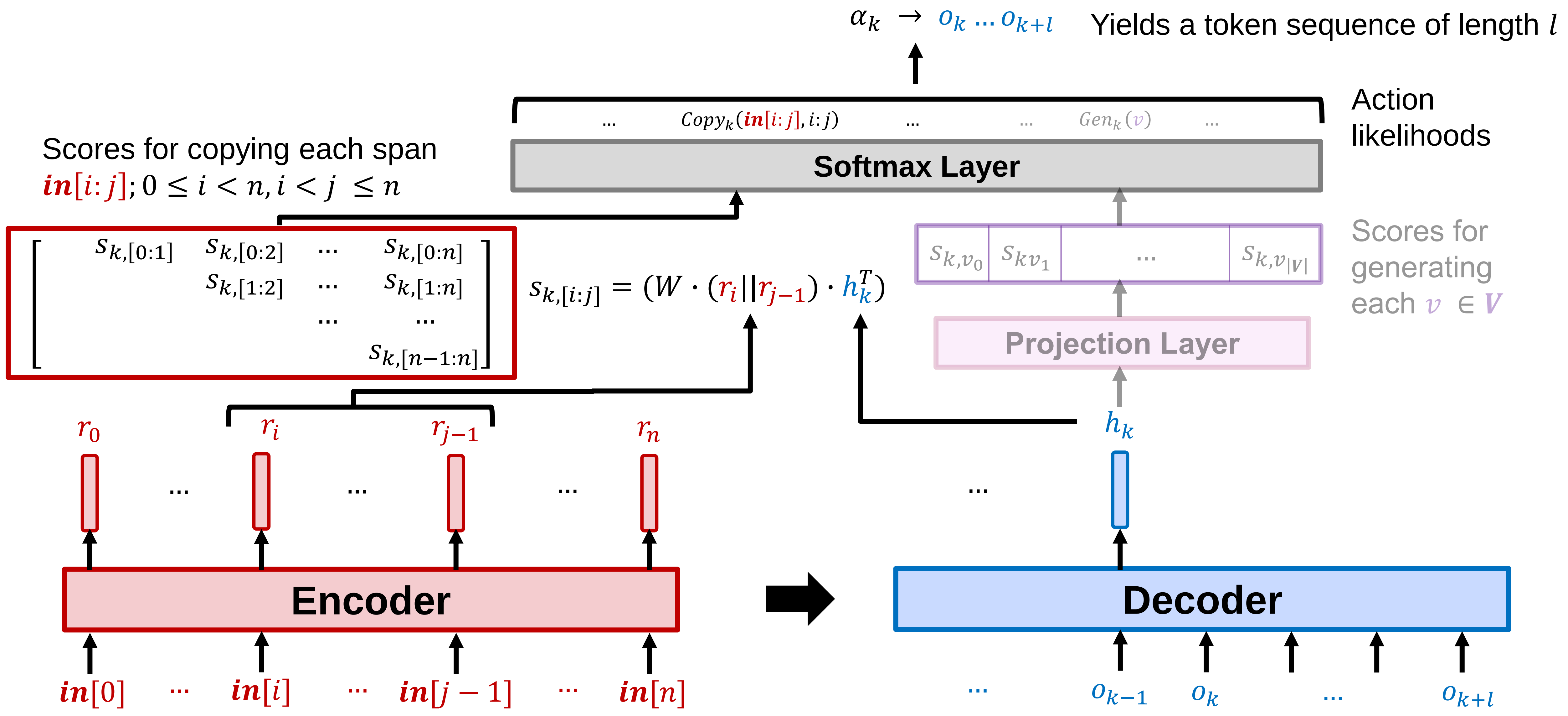

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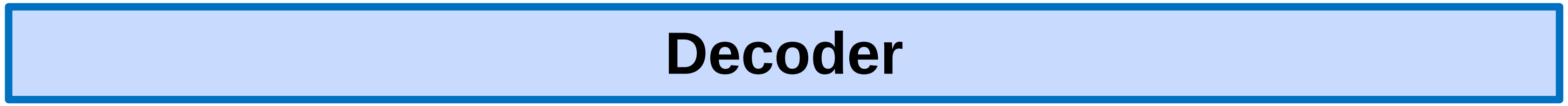

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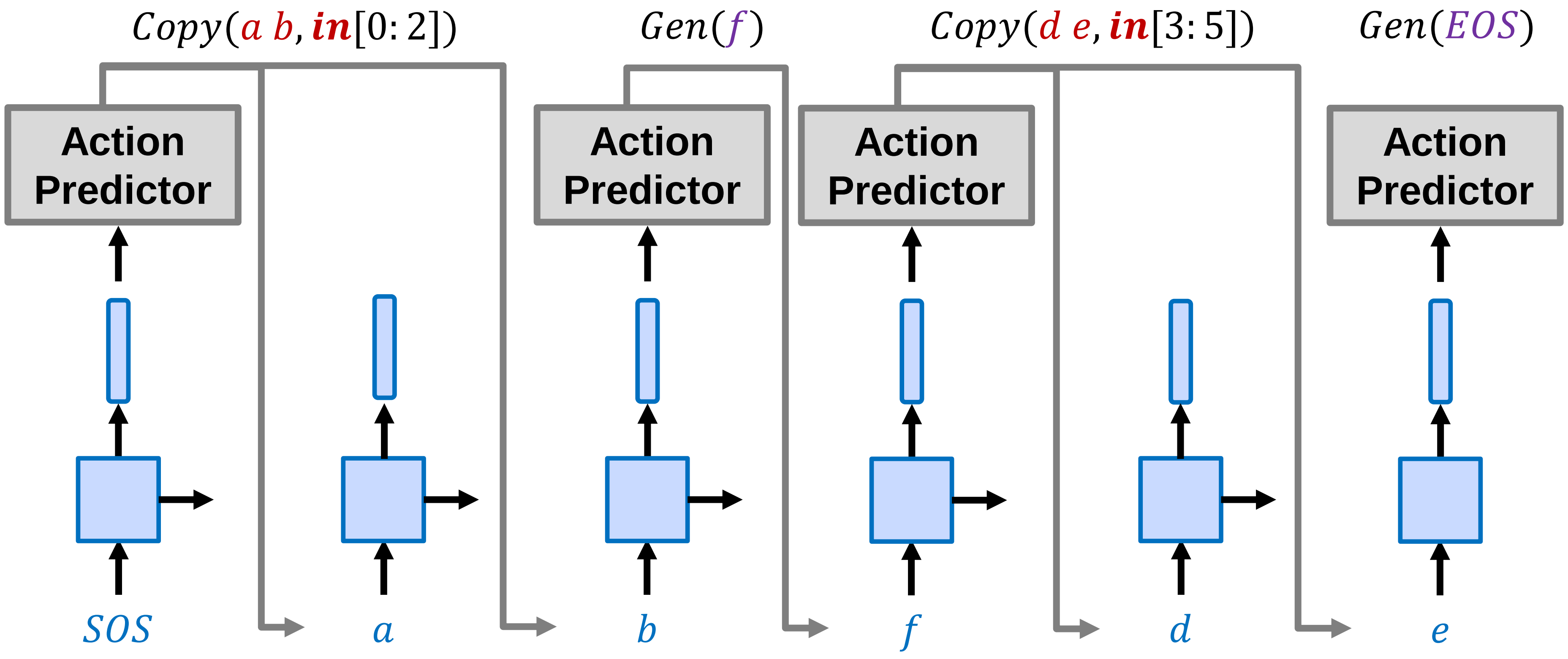

Decoder state is agnostic to predicted action

Seq2Seq + Span Copying – Training

Objective: Maximize $p(o_0 \ldots o_m \mid \boldsymbol{in})$

Zhou et al. (2018)
Predict any one of the correct actions at each step

$$\prod_{0 \le k \le m} \sum_{\alpha \in A_k} q(\alpha \mid \boldsymbol{in}, o_0 \ldots o_{k-1})$$

- Local correctness ≠ global correctness
- Not explicitly encouraging the model to rely on fewer actions

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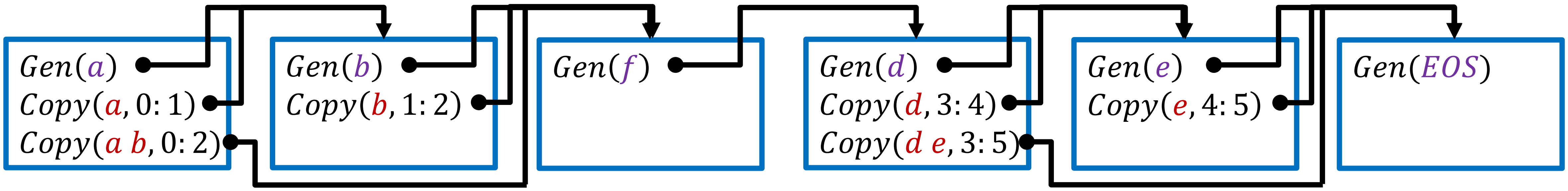

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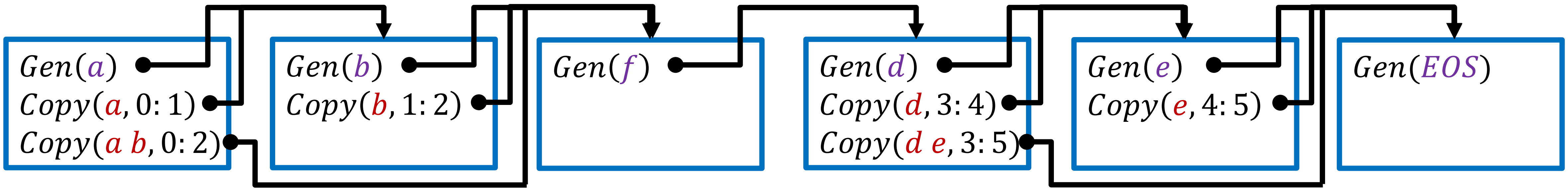
We propose…
Marginalization over all possible correct action sequences that yield $o_0 \ldots o_m$

a b c d e → a b f d e



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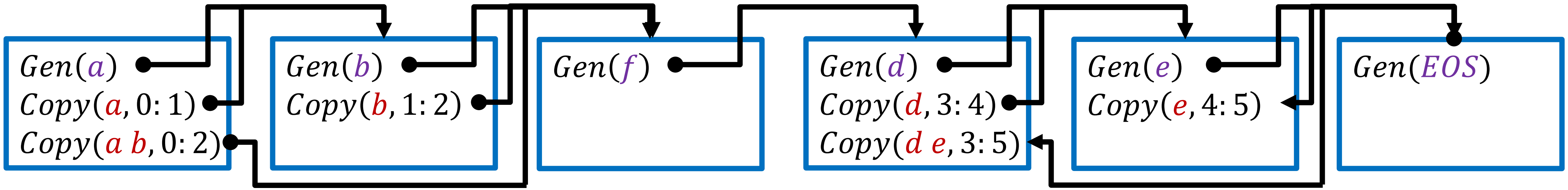

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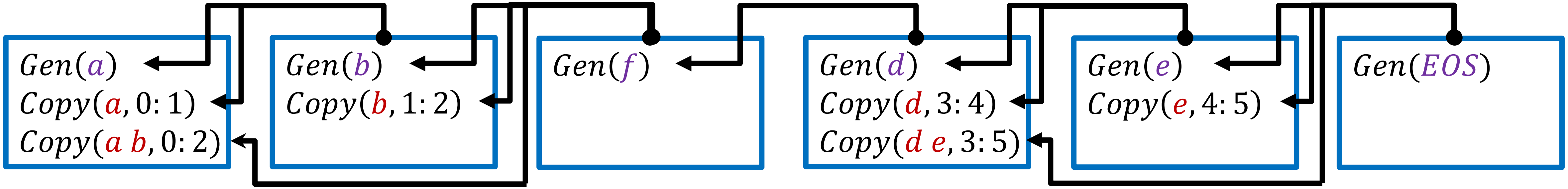
$$p(o_k \dots o_m \mid \mathbf{in}, o_0 \dots o_{k-1}) = \sum_{\substack{\alpha \in A_k \\ l = [\![\alpha]\!]}} q(\alpha \mid \mathbf{in}, o_0 \dots o_{k-1}) \times p(o_{k+l} \dots o_m \mid o_0 \dots o_{k+l-1})$$

- Probability of generating correct suffix conditioned only on subsequence generated so far, not the concrete actions
- Encourages copying longer spans through fewer # of actions

a b c d e → a b f d e

Enumerating all possible correct action sequences that yield $a\ b\ f\ d\ e$



$p(EOS \mid \mathbf{in}, a\ b\ f\ d\ e)$

$p(e \mid \mathbf{in}, a\ b\ f\ d)$

$p(d\ e \mid \mathbf{in}, a\ b\ f)$

$p(f\ d\ e \mid \mathbf{in}, a\ b) = [Gen(f) \times p(d\ e \mid \mathbf{in}, a\ b\ f)]$

$p(b\ f\ d\ e \mid \mathbf{in}, a) = [Gen(b) \times p(f\ d\ e \mid \mathbf{in}, a\ b)] + [Copy(b, 1:2) \times p(f\ d\ e \mid \mathbf{in}, a\ b)]$

$$p(a\ b\ f\ d\ e \mid \mathbf{in}) = [Gen(a) \times p(b\ f\ d\ e \mid \mathbf{in}, a)] + [Copy(a, 0:1) \times p(b\ f\ d\ e \mid \mathbf{in}, a)] + [Copy(a\ b, 0:2) \times p(f\ d\ e \mid \mathbf{in}, a\ b)]$$

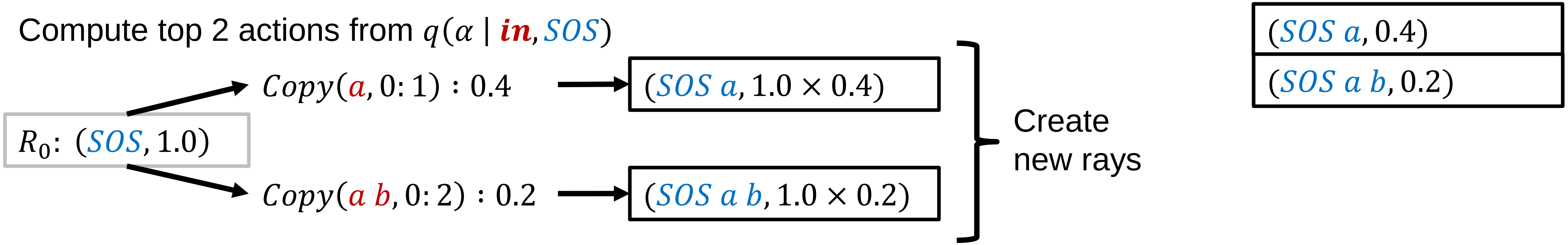
Seq2Seq + Span Copying – Inference

Generate likely action sequences through beam search

- Action sequences of the same length could yield token sequences of varying length
  → **Explicitly maintain token sequence length and "pause" expansion when needed**
- Different action sequences could yield identical token sequences
  → **"Merge" rays yielding identical token sequences**

Iteration 1: Beam $= [R_0\colon (SOS, 1.0)]$ $l = 1$ ***in***: a b c d e Beam width = 2

Compute top 2 actions from $q(\alpha \mid \boldsymbol{in}, SOS)$



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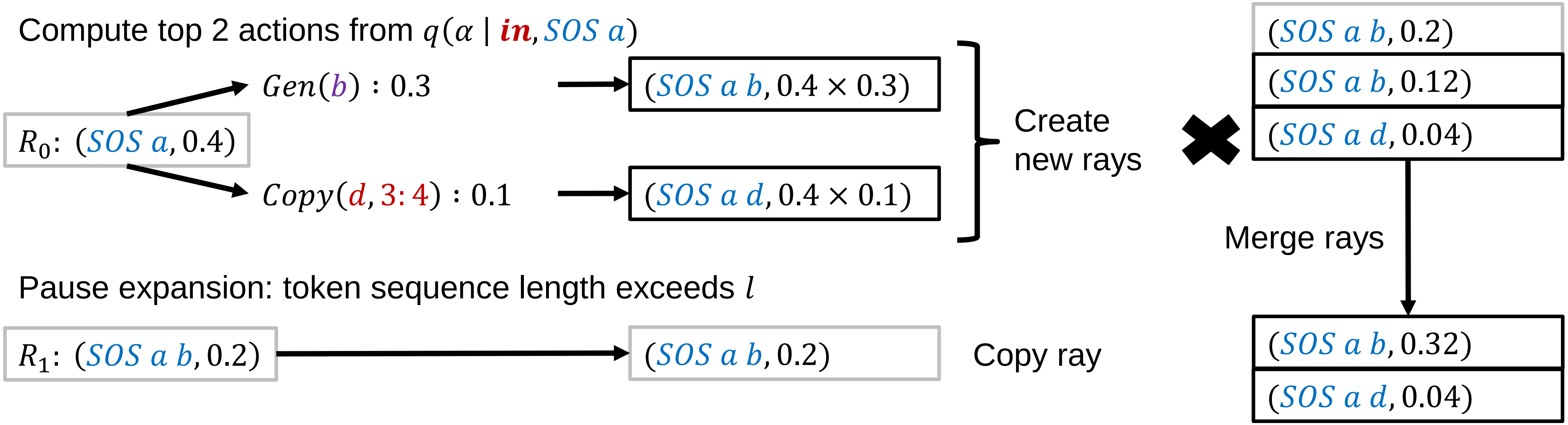
Iteration 2: Beam $= [R_0\colon (SOS\ a, 0.4),\ R_1\colon (SOS\ a\ b, 0.2)]$ $l = 2$ ***in***: a b c d e Beam width = 2



Experimental Evaluation: Bug Fixing

Bug fixing: Given a faulty version of the code, generate the corrected version.

in

```
public boolean equals(Object obj) {
    return this.equals(obj);
}
```

out

```
public boolean equals(Object obj) {
    if (obj == null)
        return false;
    return this.equals(obj);
}
```

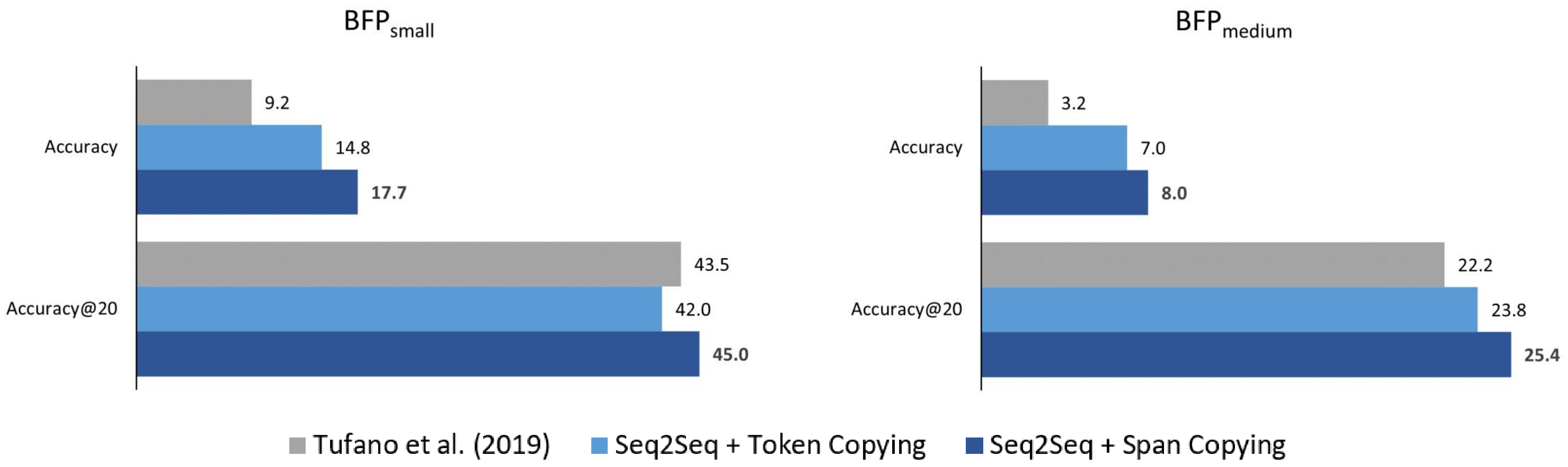
Bug-fix pair (BFP) datasets *(Tufano et al., 2019*) consisting of Java code snippets:

- $\textbf{BFP}_{\textbf{small}}$: ≤ 50 code tokens
- $\textbf{BFP}_{\textbf{medium}}$: 50-150 code tokens

Experimental Evaluation: Bug Fixing

Baselines:

- Tufano et al. (2019): Seq2Seq w/ no copy mechanism
- Seq2Seq + Token Copying: Seq2Seq w/ copying single tokens



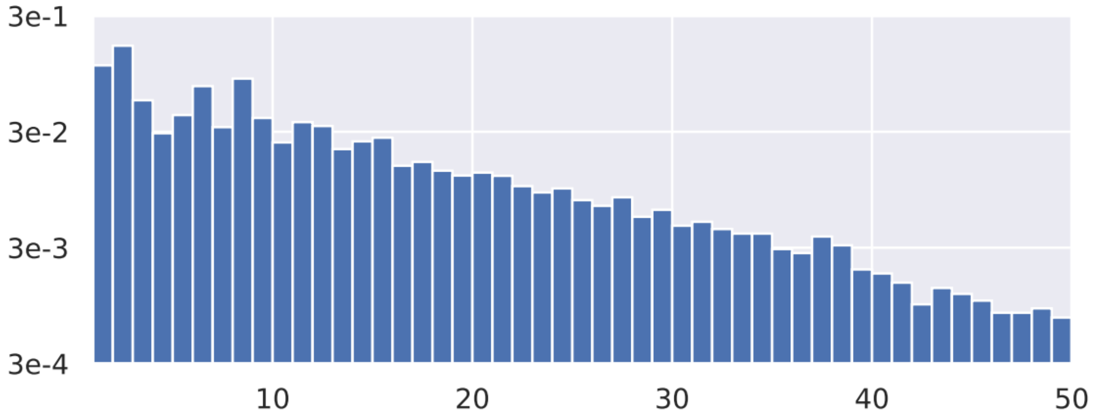
Seq2Seq + Span Copying outperforms baselines, achieving new state-of-the-art on BFP datasets

Experimental Evaluation: Bug Fixing

Lengths of spans corresponding to $Copy$ actions during beam decoding in log-y scale

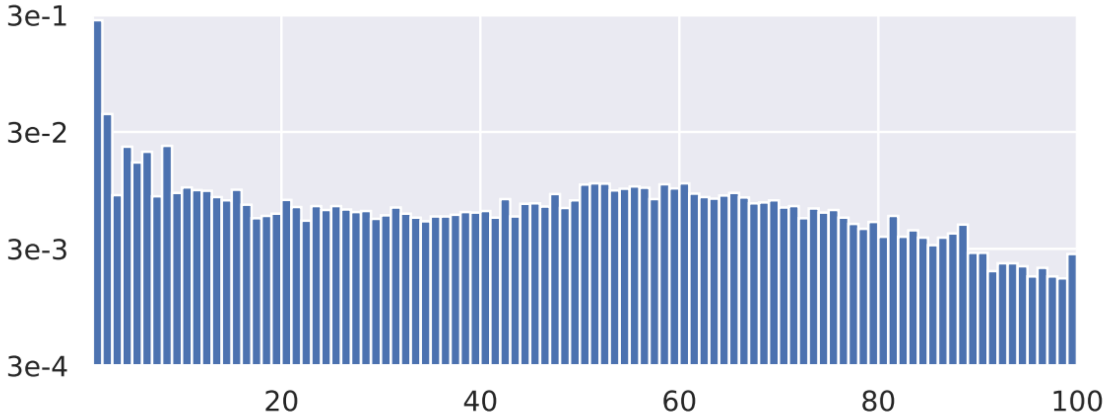
BFP_{small}:

- μ = 9.6, median = 7
- 11.2% of $Copy$ actions correspond to spans of length 1



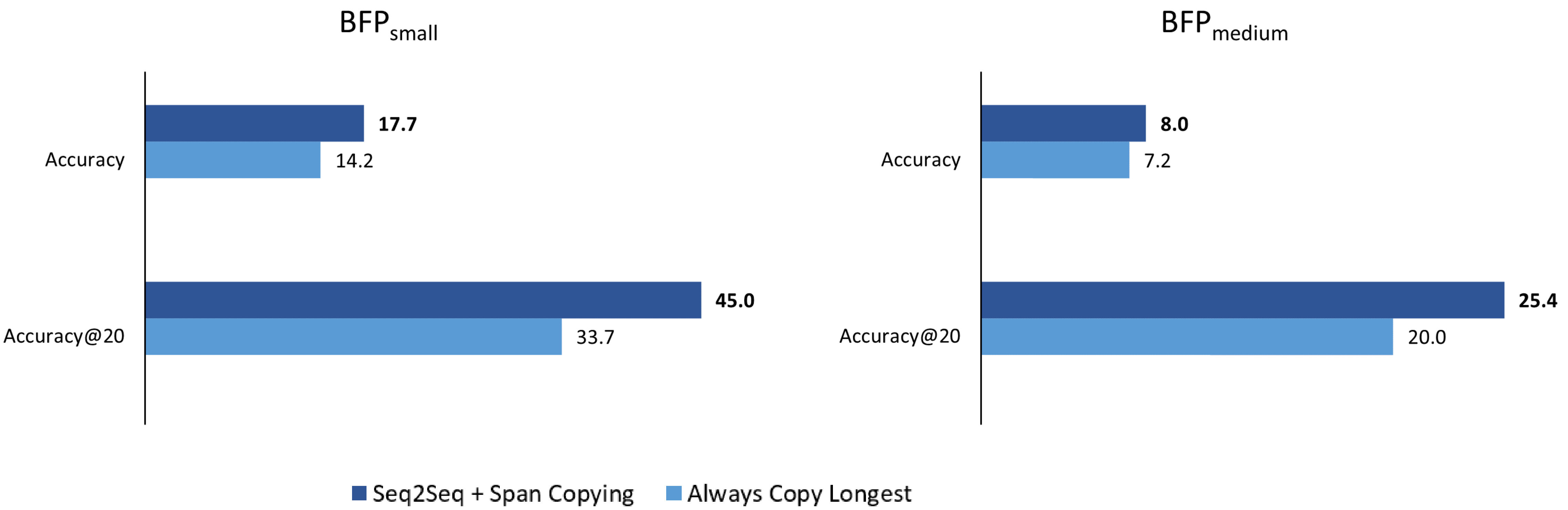
BFP_{medium}:

- μ = 29.5, median = 19
- 27.1% of $Copy$ actions correspond to spans of length 1



$Copy$ actions tend to yield long copy spans

Experimental Evaluation: Bug Fixing



- **Heuristic *Copy* action selection fails to capture the entire spectrum of correct actions.**

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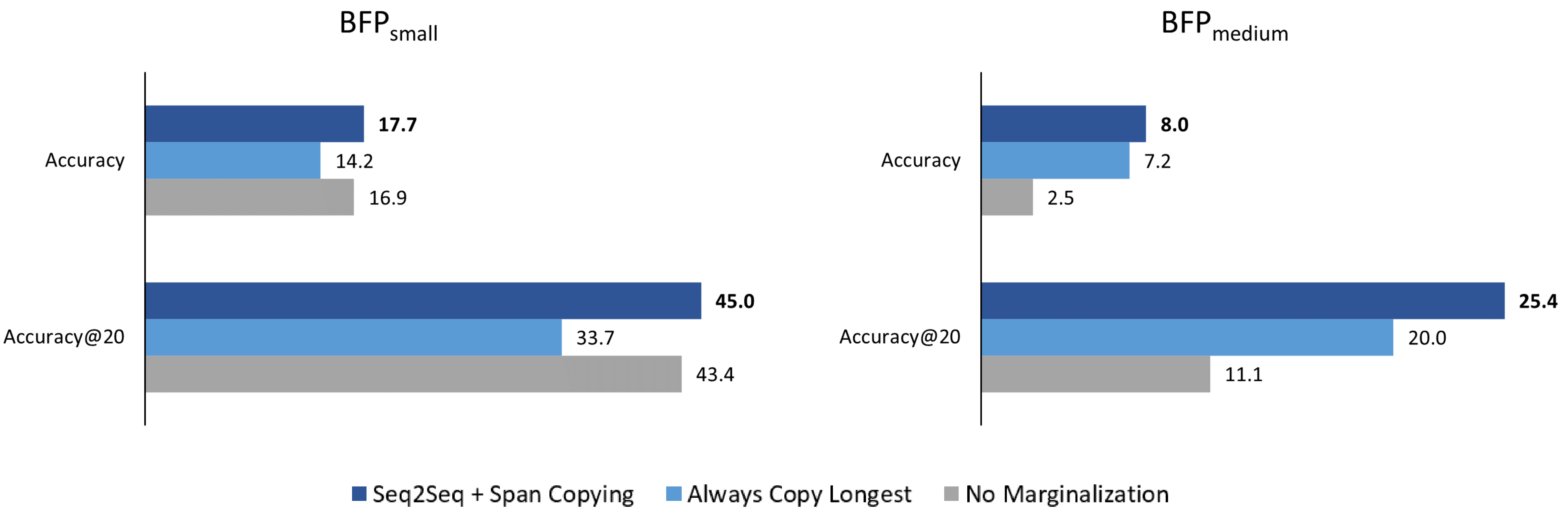
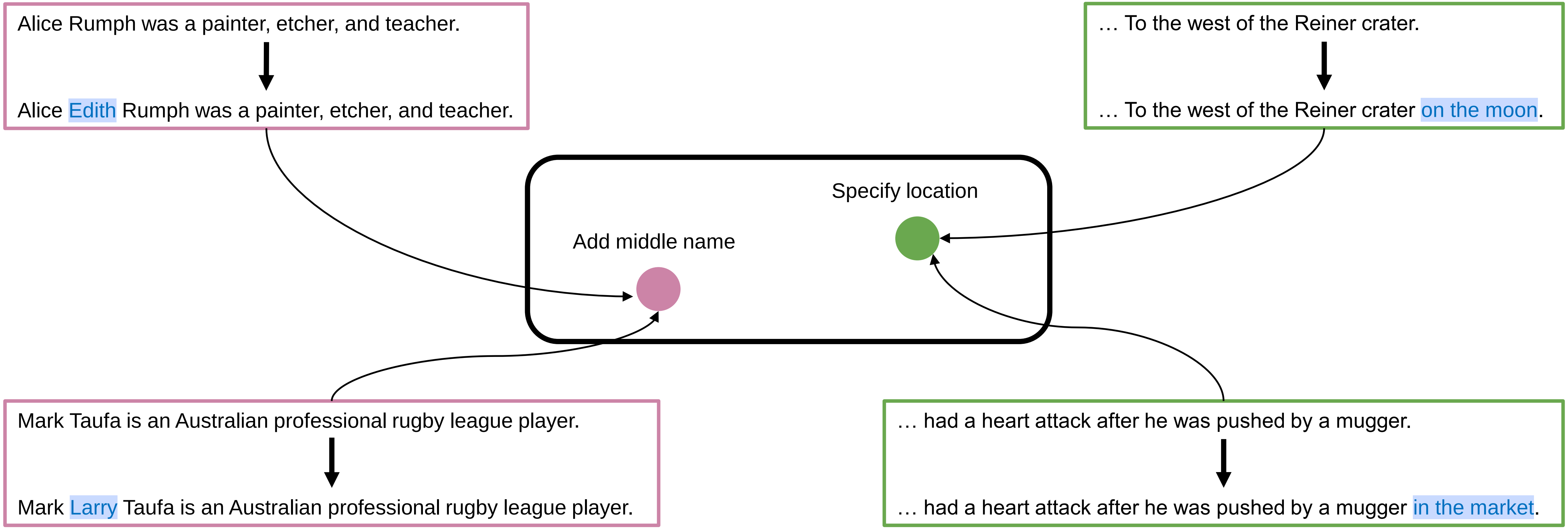


- **Heuristic *Copy* action selection fails to capture the entire spectrum of correct actions.**
- **Marginalization incentivizes the model to use as few actions as possible.**

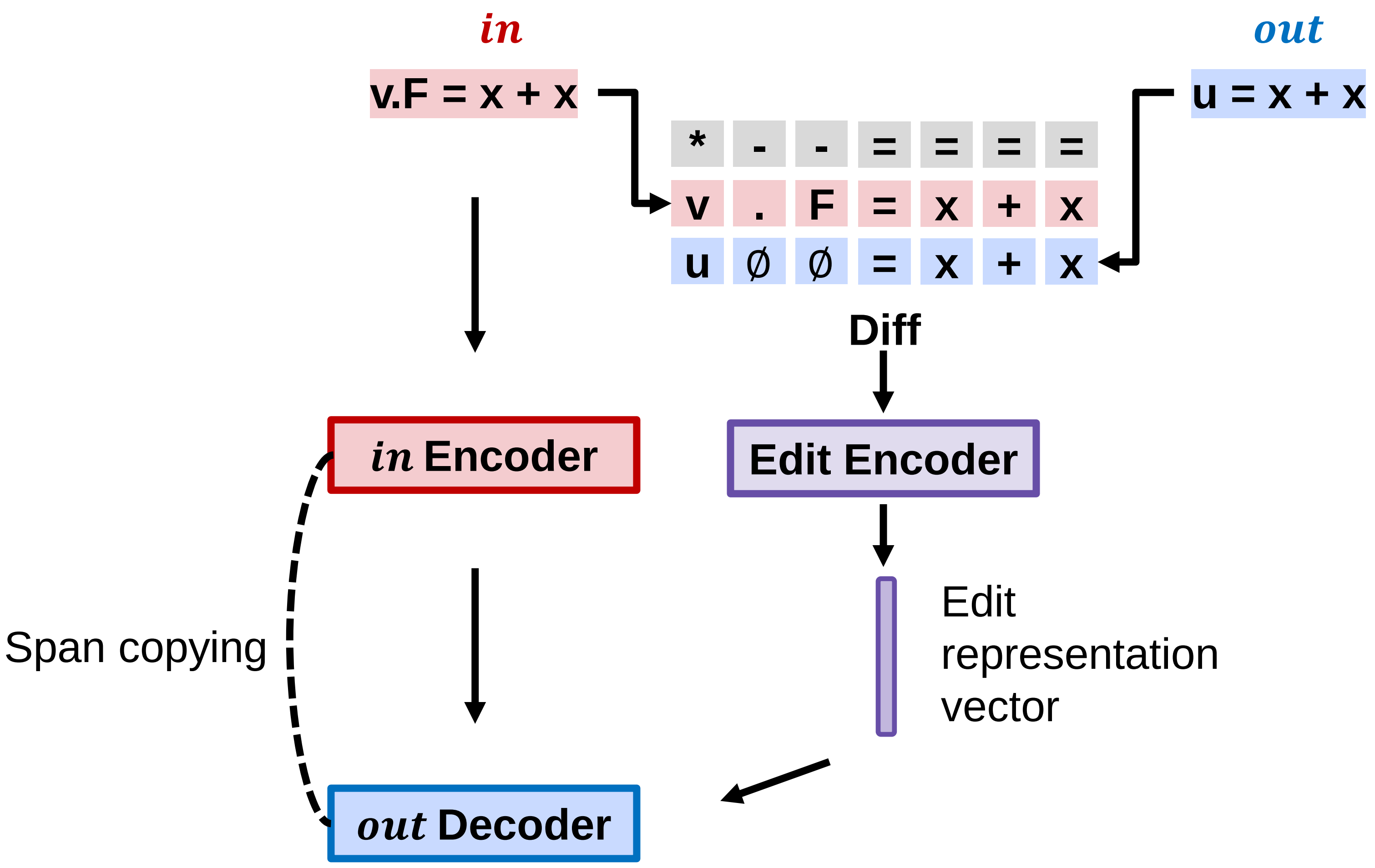
Experimental Evaluation: Learning Edit Representations

Learn to embed similar edit patterns nearby in a vector space



Experimental Evaluation: Learning Edit Representations

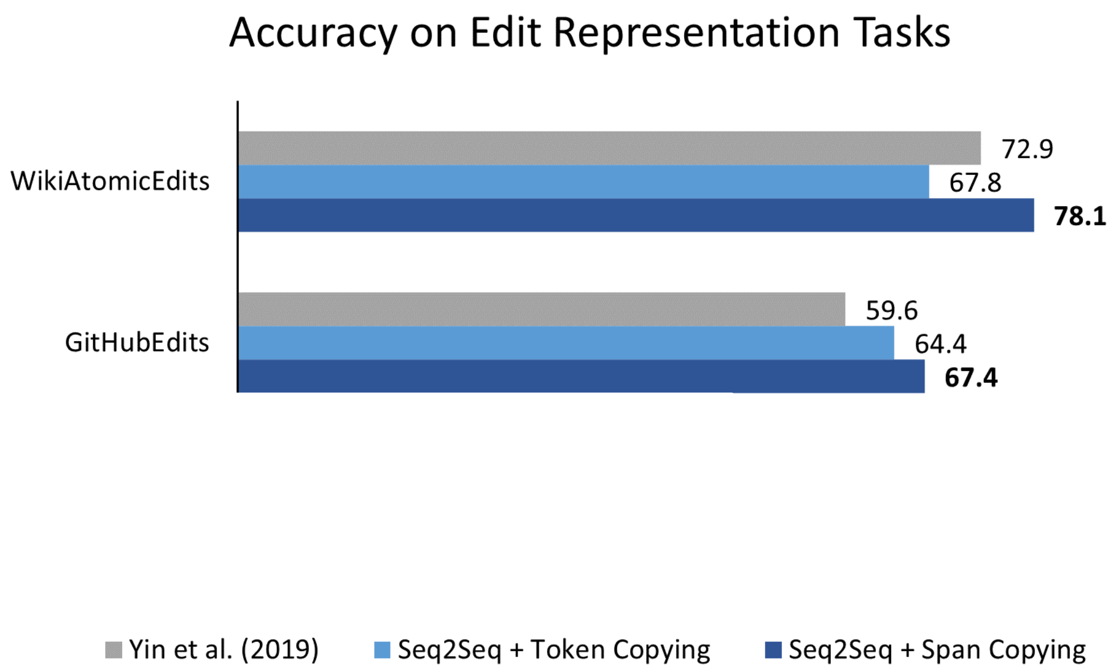
Autoencoder-like model structure *(Yin et al., 2019)*



Experimental Evaluation: Learning Edit Representations

Datasets:

- WikiAtomicEdits *(Faruqui et al., 2018)*
- GitHubEdits *(Yin et al., 2019)*
- C# Fixers *(Yin et al., 2019)* (eval only)



Span copying…

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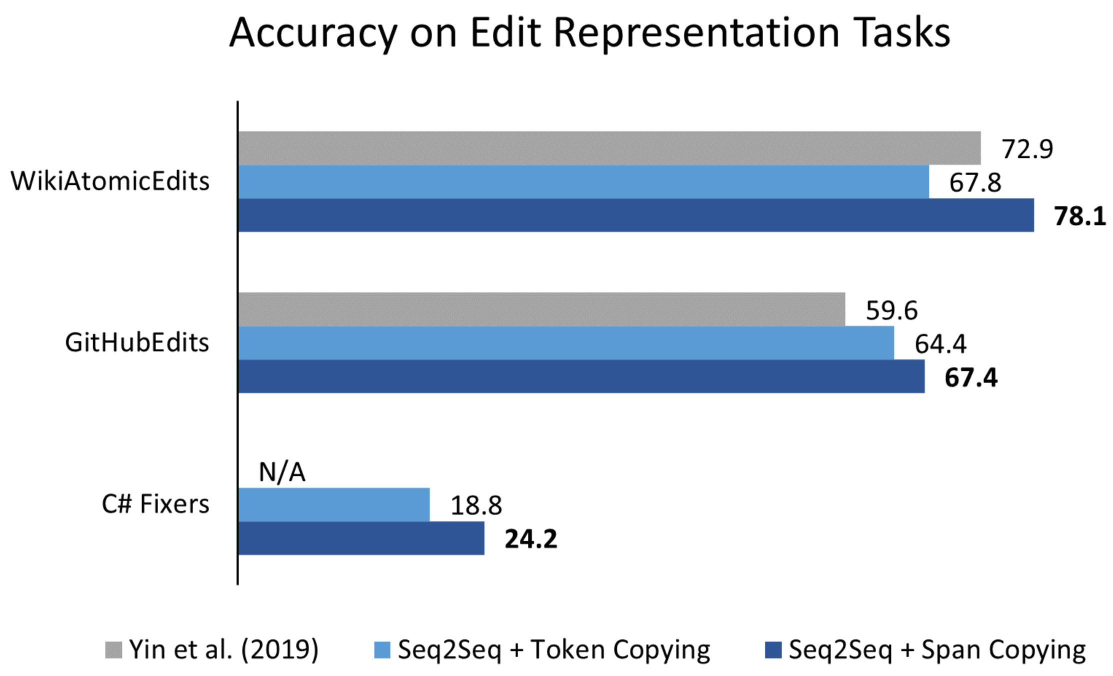

Span copying…

- Allows a model to more accurately predict edited text and code
- Facilitates learning more generalizable edit representations

Summary

- Span-copying mechanism which can be integrated with common encoder-decoder architectures.
- Marginalization for training encourages decoder to copy long spans.
- Beam search variant which is better suited for this setting.
- Approach leads to improved performance for editing tasks.

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