Detecting Local Insights from Global Labels: Supervised & Zero-Shot Sequence Labeling via a Convolutional Decomposition

Allen Schmaltz

Harvard University

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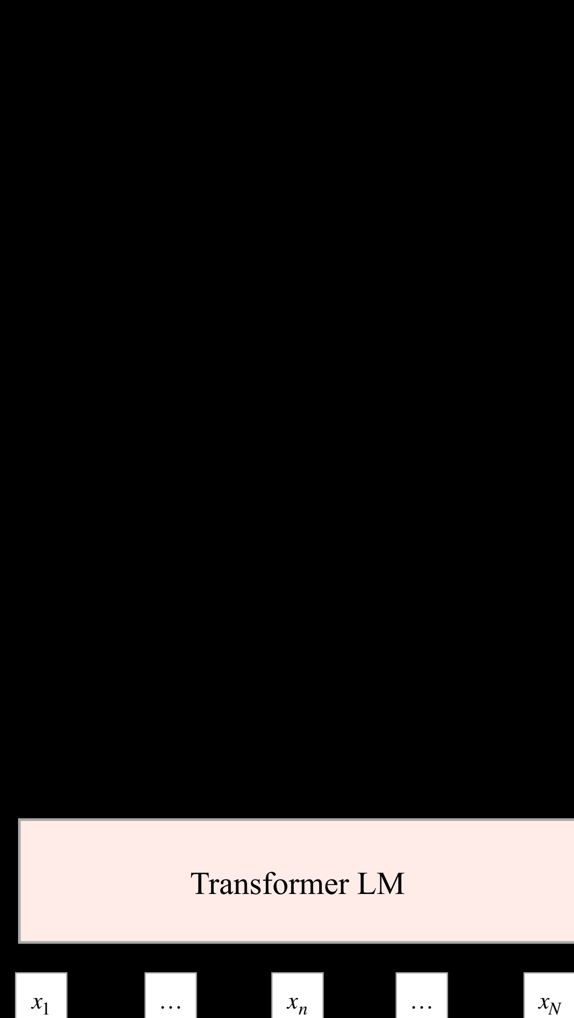
Computational Linguistics (2021)

Version 1.0

Horizontal (across the input) & *Vertical* (across the support set) Model Decompositions



Document-level label (Y) available for training (but not at test time)

Input document (N tokens)

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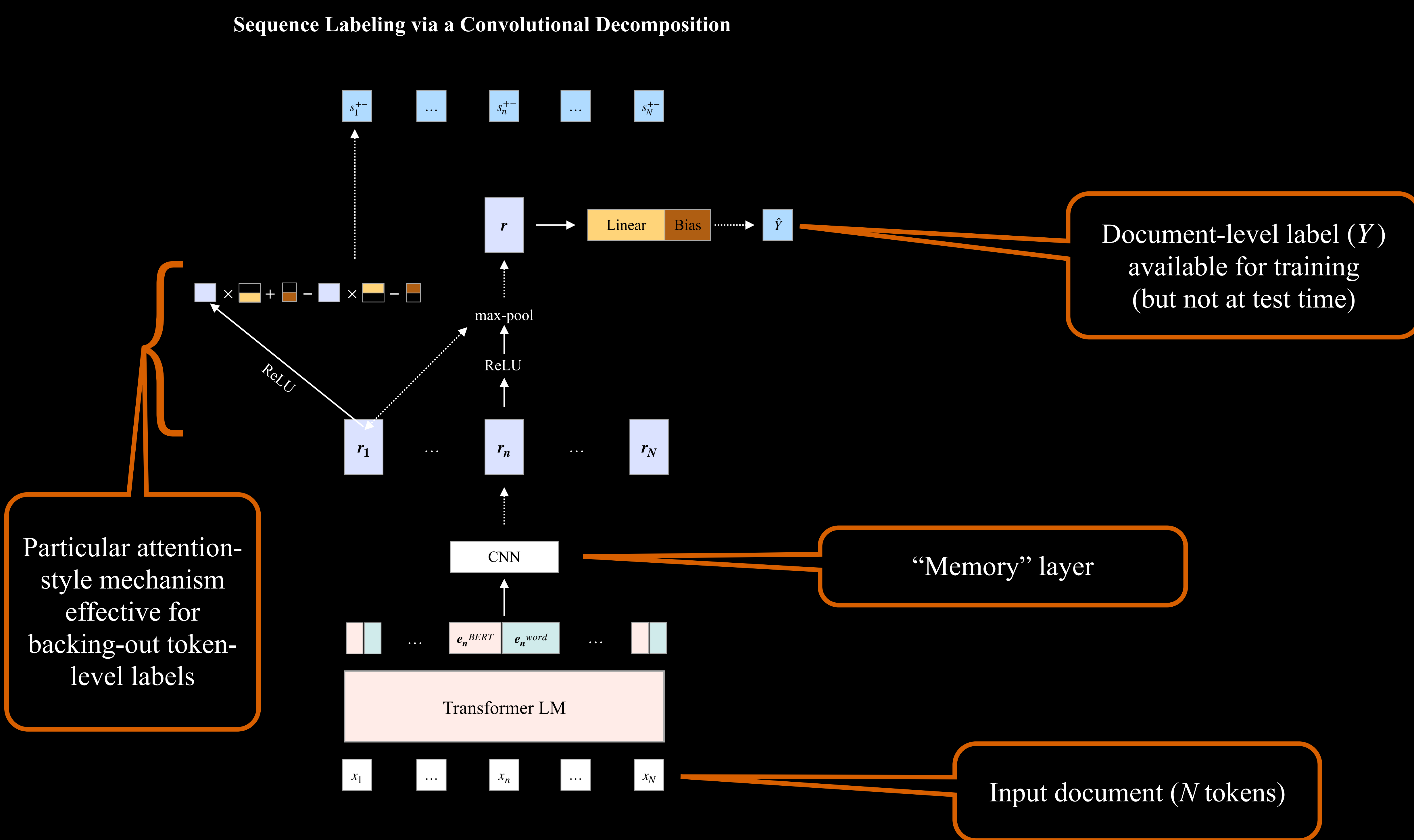

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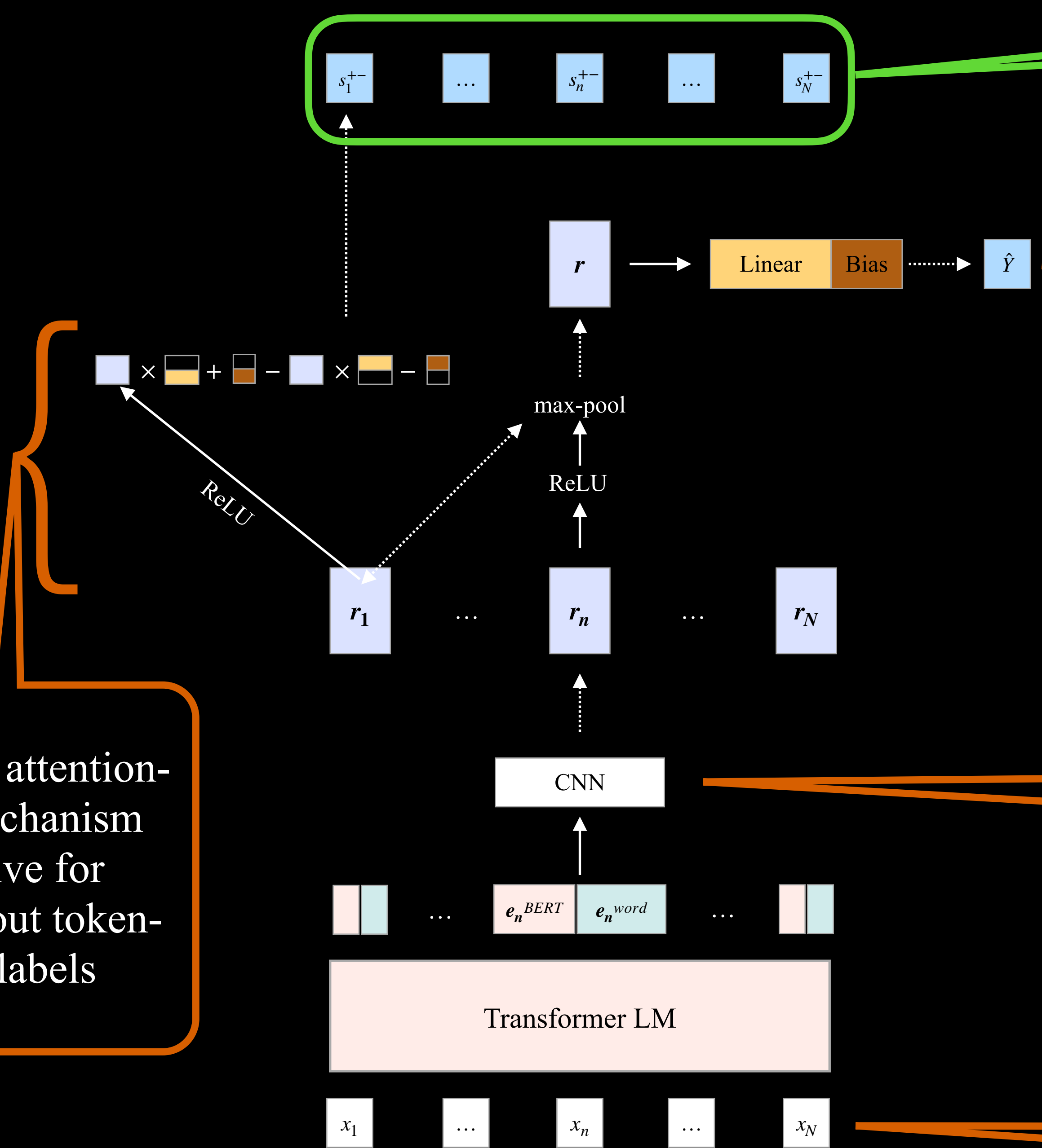
Horizontal (across the input) & *Vertical* (across the support set)
Model Decompositions

Sequence Labeling via a Convolutional Decomposition



Predict: token-level labels (y_n)
(Hidden from training and test)

Document-level label (Y)
available for training
(but not at test time)

Particular attention-style mechanism effective for backing-out token-level labels

"Memory" layer

Input document (N tokens)

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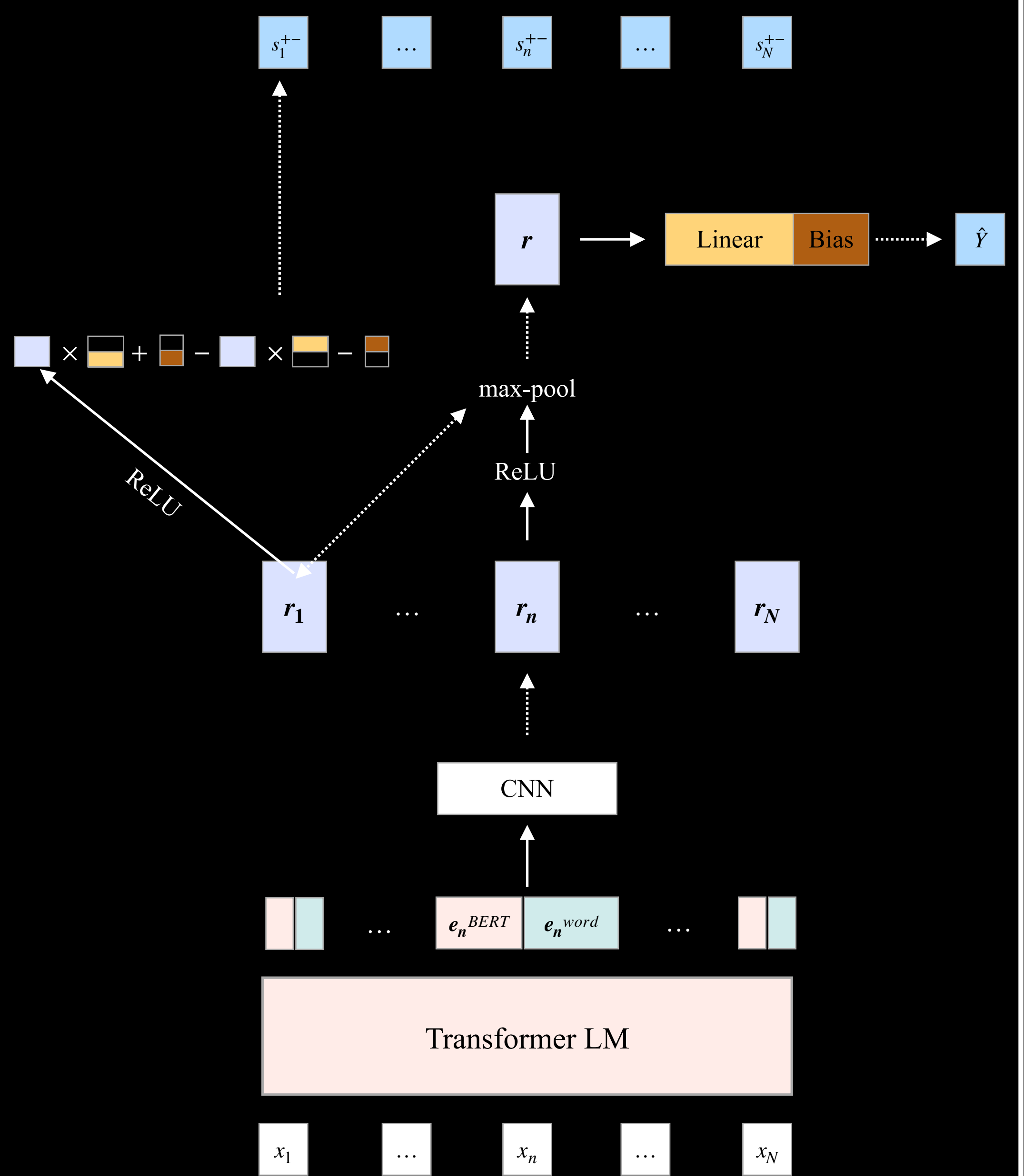

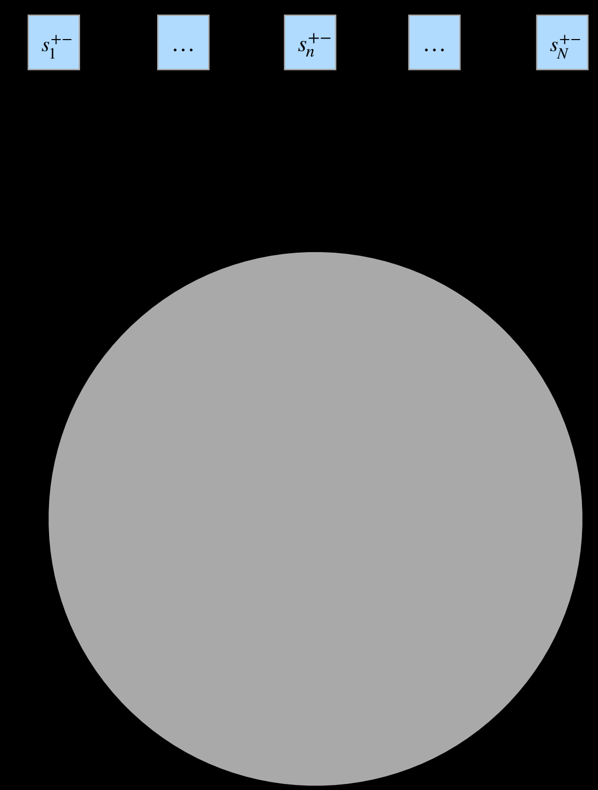

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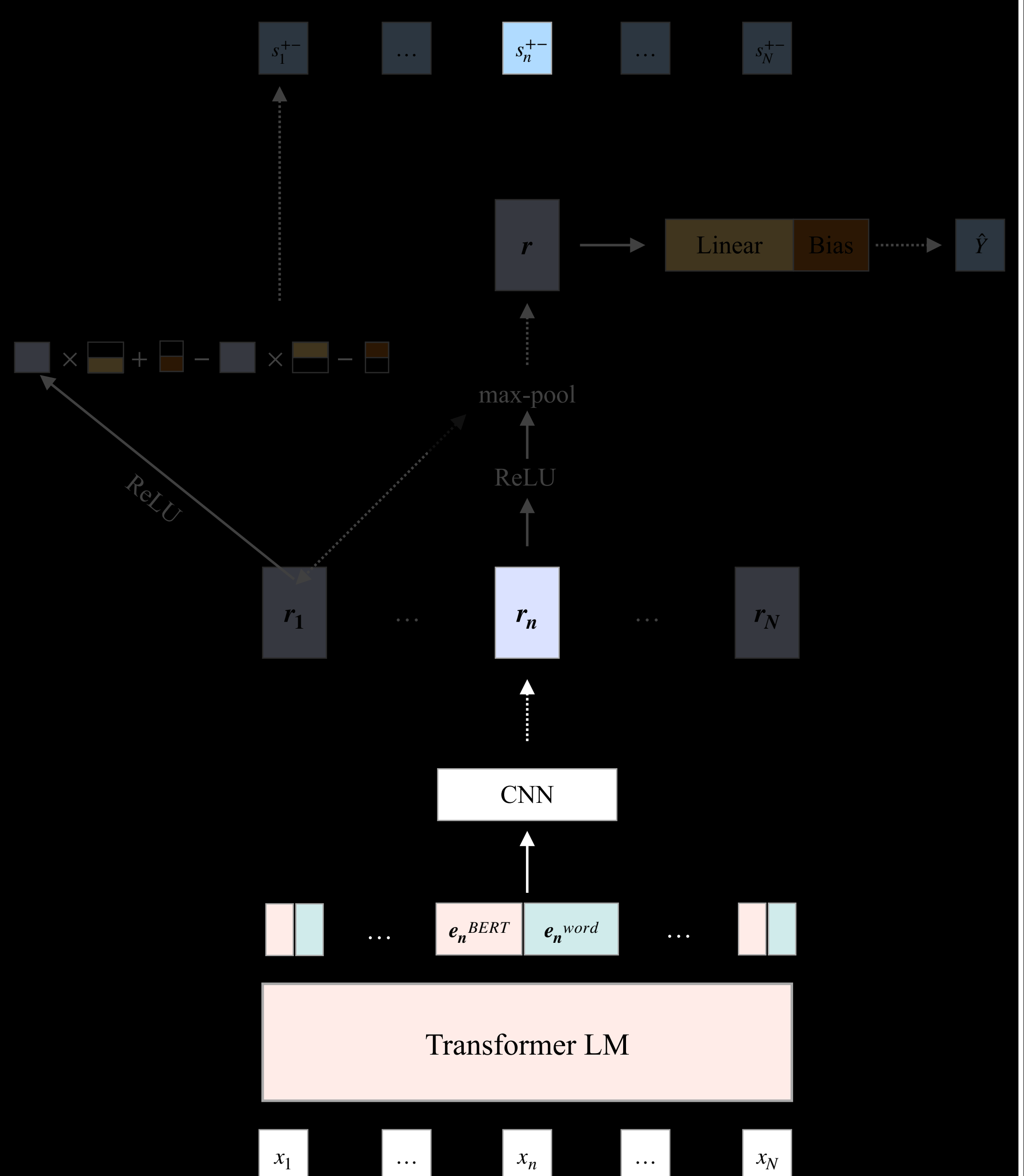

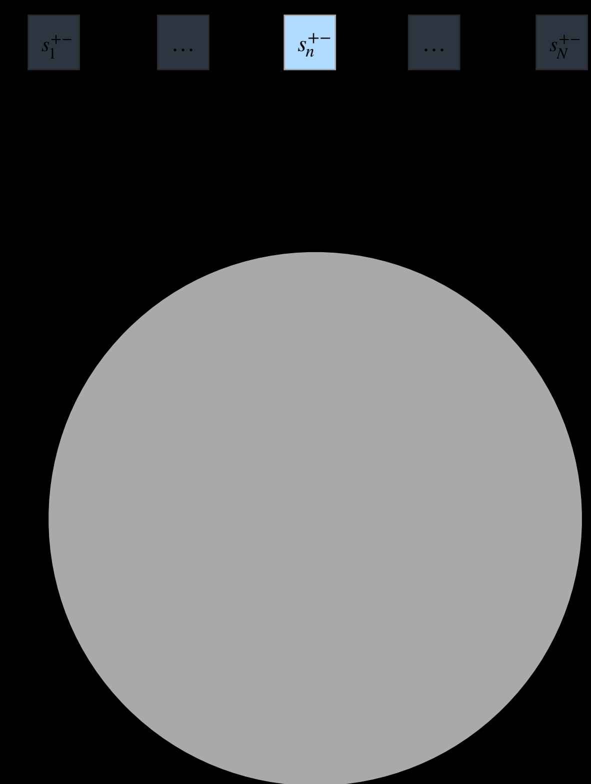

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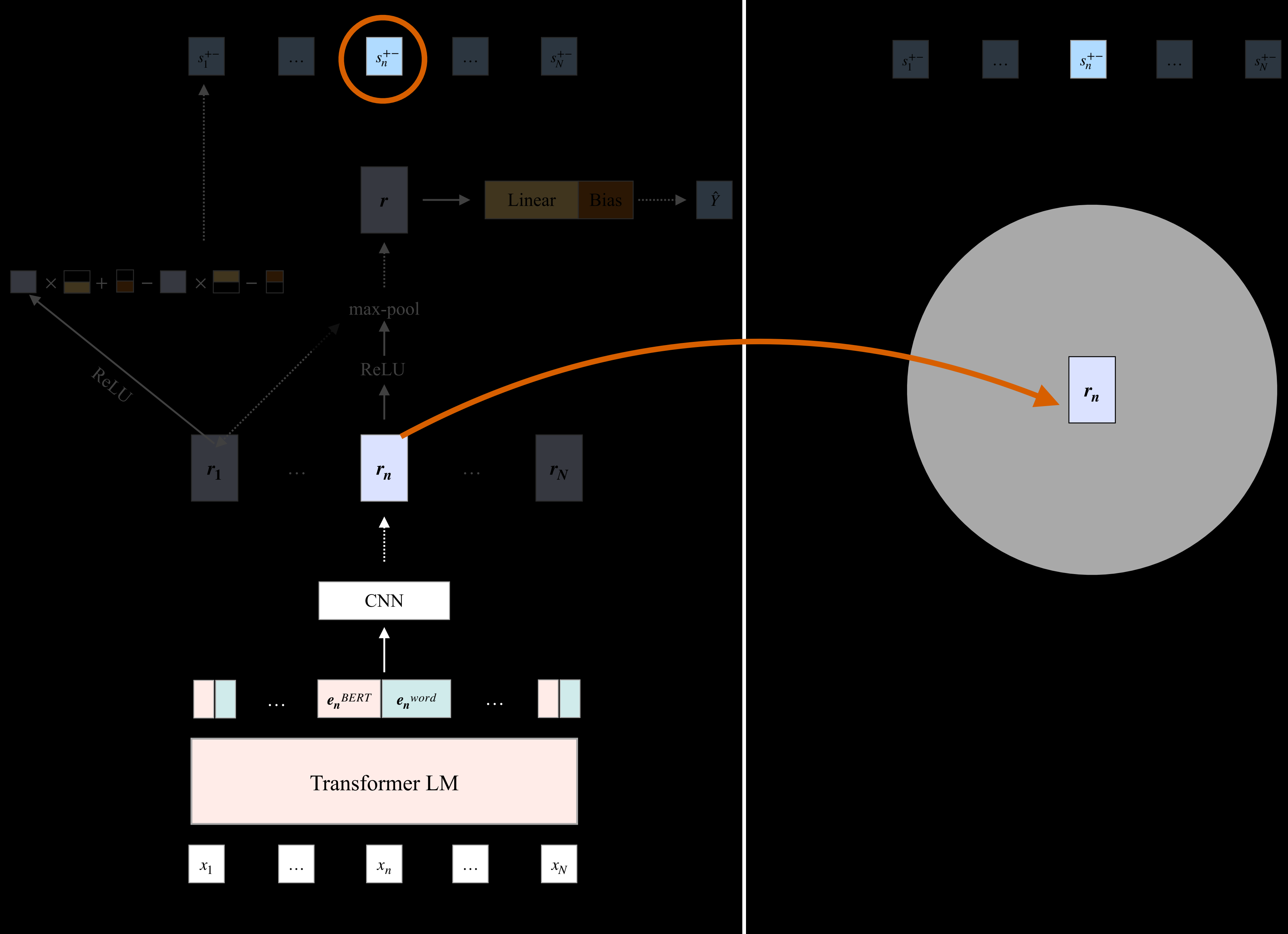

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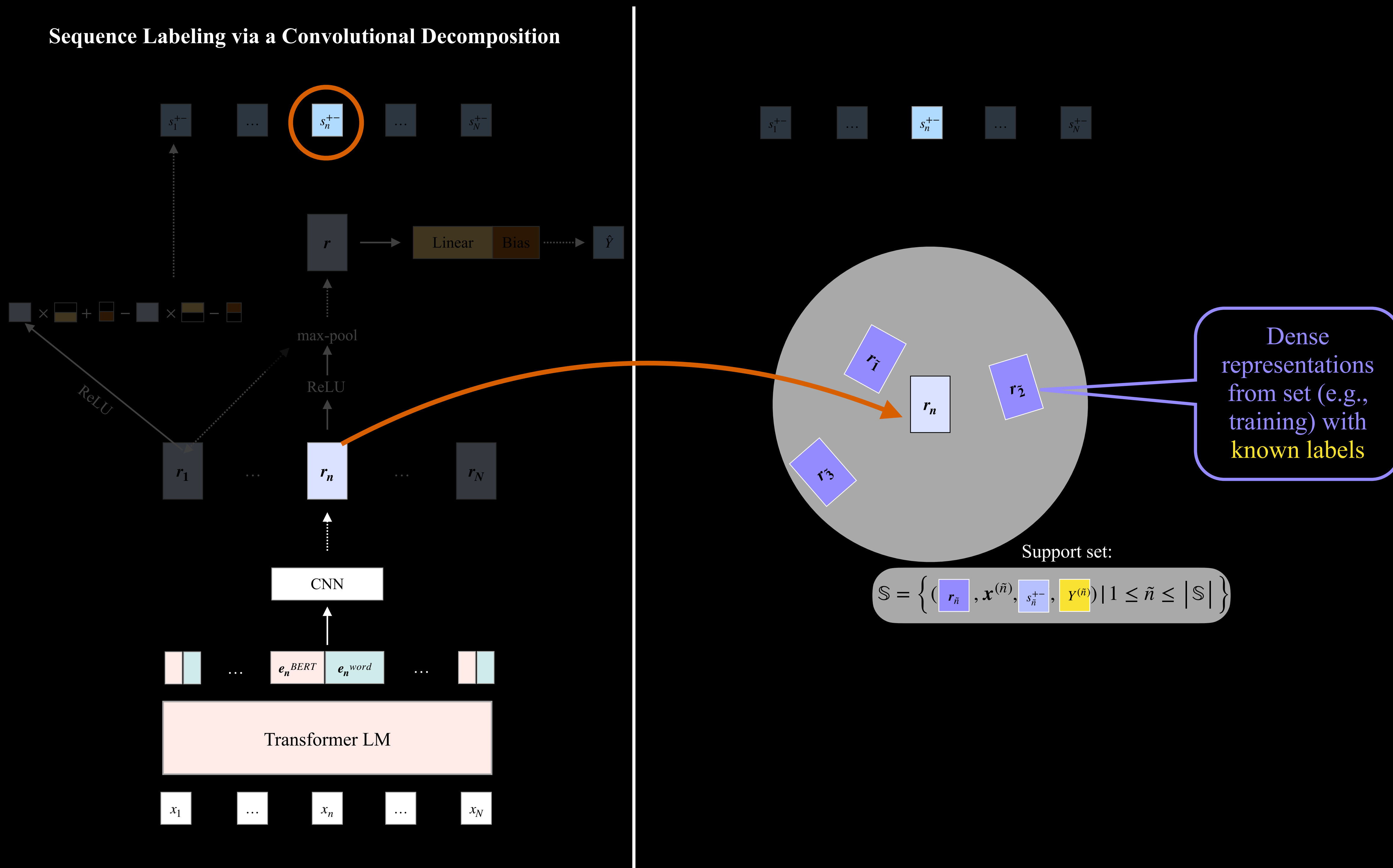

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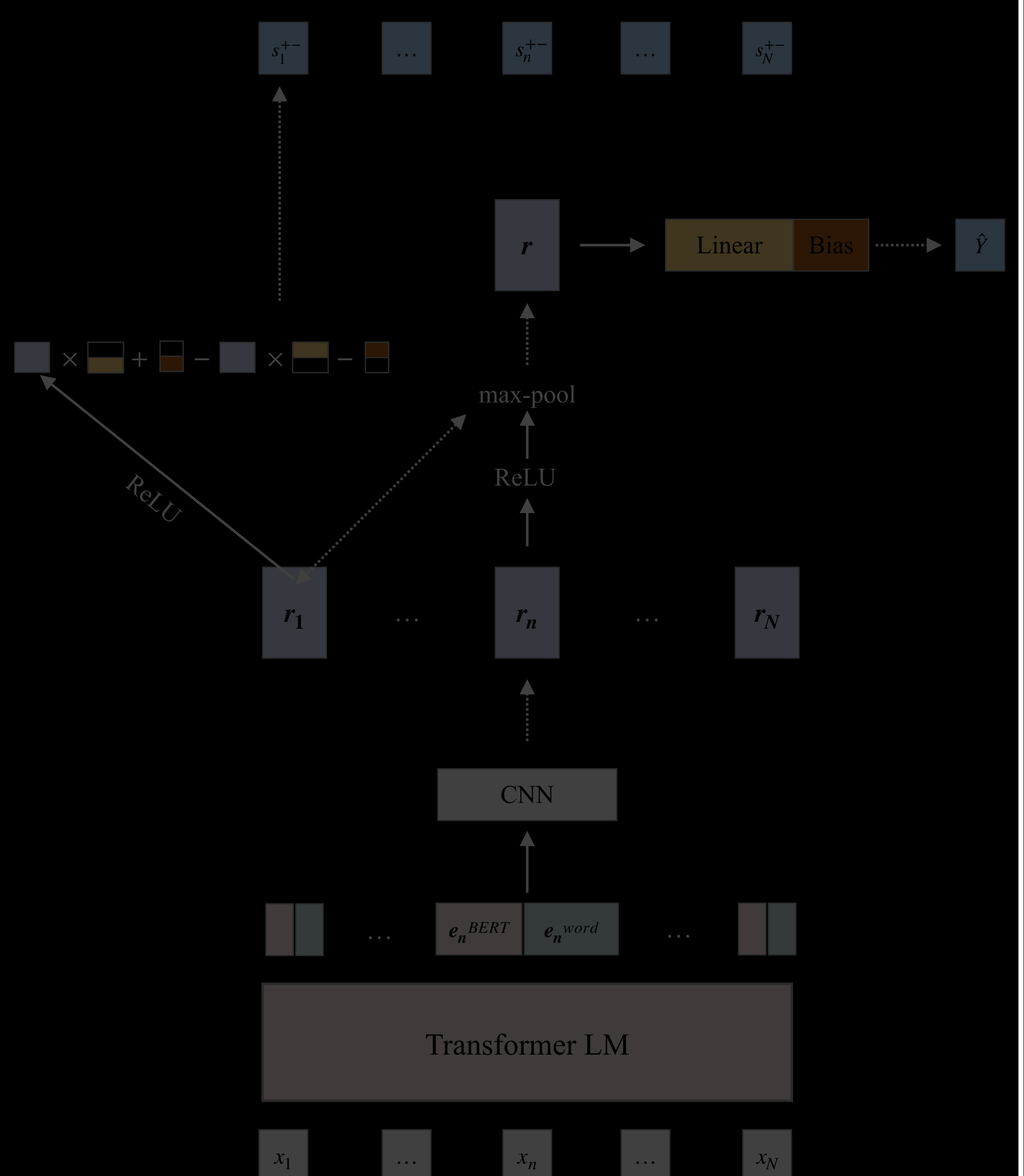
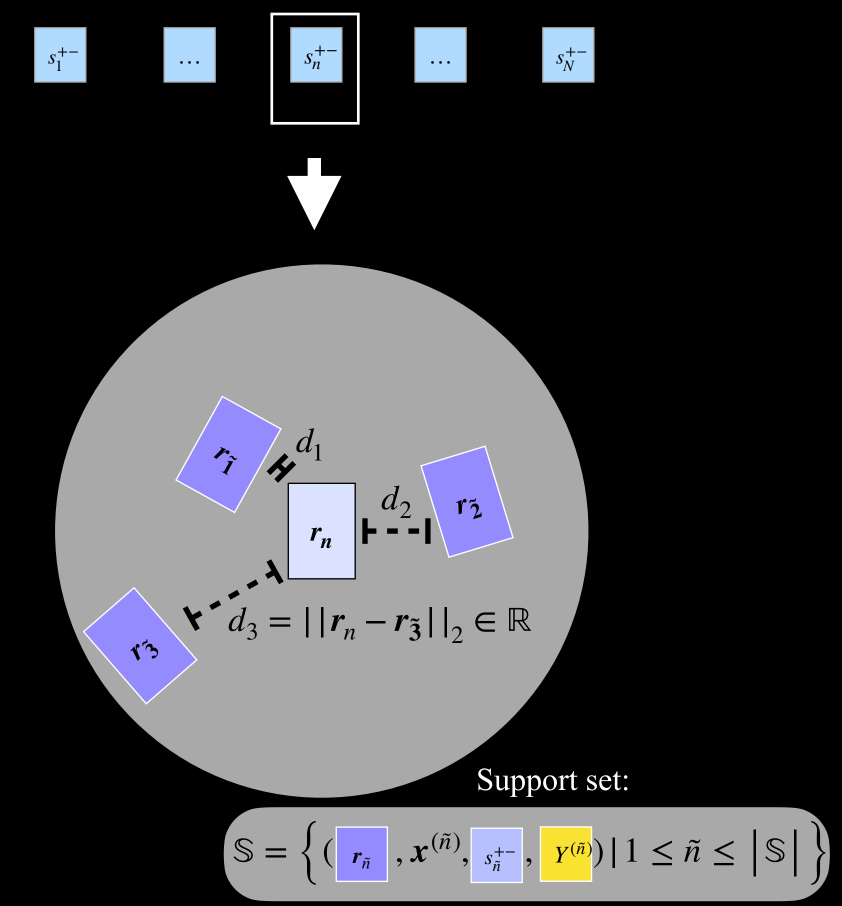


K-NN Approximation



$$\begin{aligned}\boxed{s_n^{+-}} \approx \beta &+ w_1 \cdot \left(\tanh(\boxed{s_{\tilde{1}}^{+-}}) + \gamma \cdot \boxed{Y^{(\tilde{1})}}\right)\\ &+ w_2 \cdot \left(\tanh(\boxed{s_{\tilde{2}}^{+-}}) + \gamma \cdot \boxed{Y^{(\tilde{2})}}\right)\\ &+ w_3 \cdot \left(\tanh(\boxed{s_{\tilde{3}}^{+-}}) + \gamma \cdot \boxed{Y^{(\tilde{3})}}\right)\end{aligned}$$

$$w_k = \frac{\exp(-d_k/\tau)}{\sum_{k'=1}^{3} \exp(-d_{k'}/\tau)}$$

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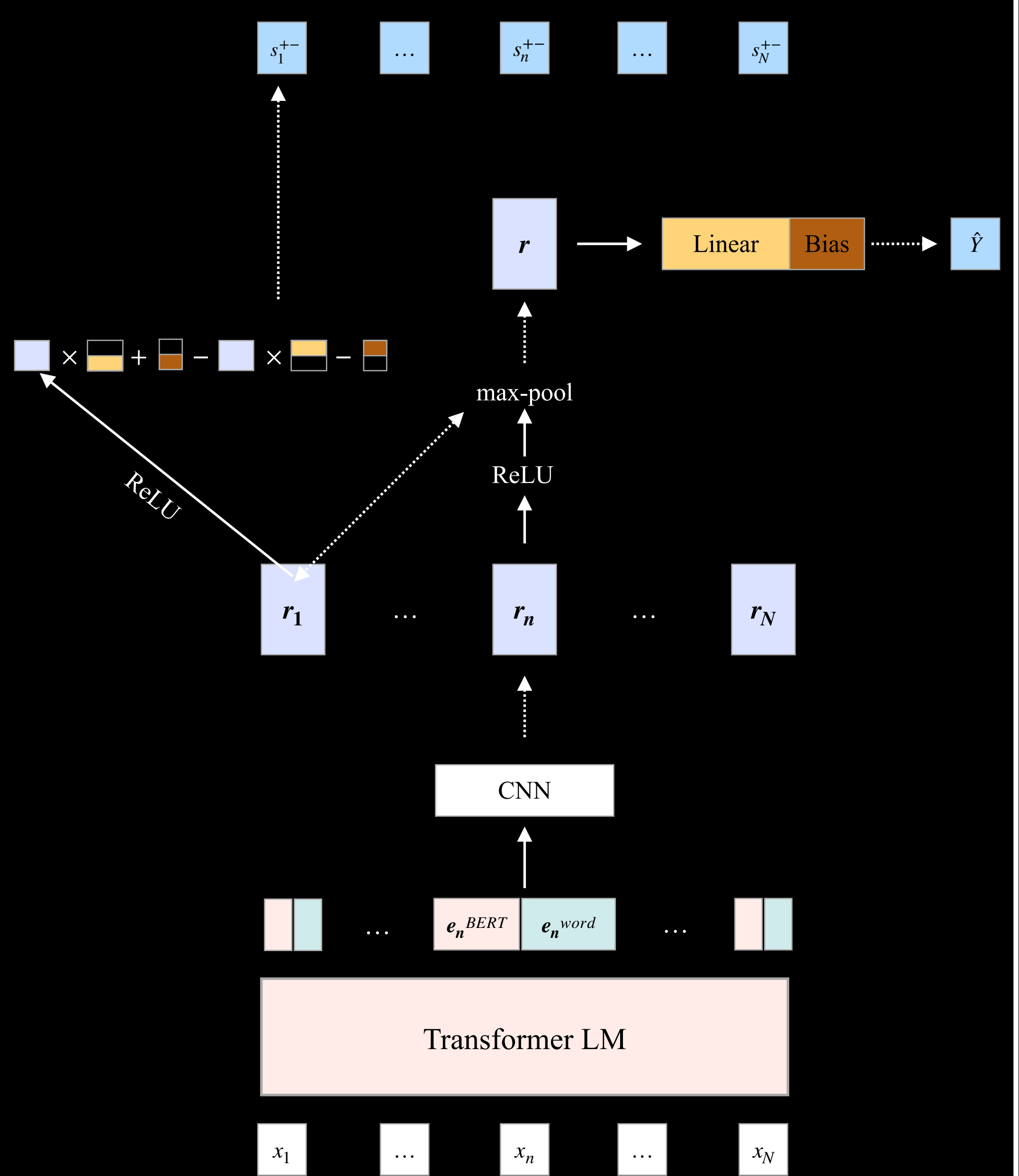

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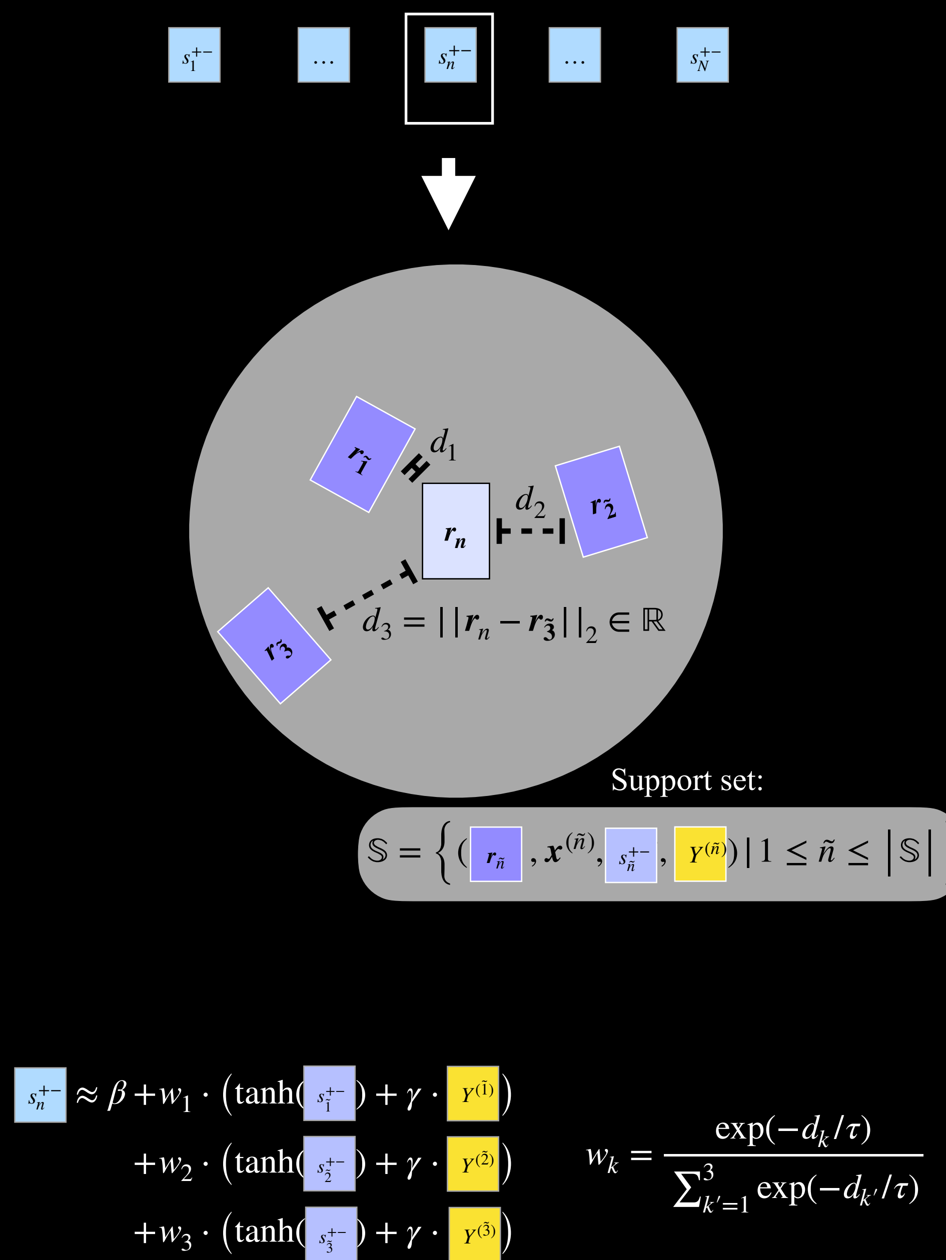

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Plan

- Task: Zero-shot sequence labeling
  - Running example: Grammatical errer [1] detection

Plan

- Task: Zero-shot sequence labeling
  - Running example: Grammatical error detection
- Decomposition across the input
- Decomposition across the support set
- Unique properties (added to the standard deep networks):
  - Analyze data at lower resolutions than available labels
  - Out-of-domain (OOD) detection / prediction reliability heuristics
  - Updatability

Task: Zero-Shot Binary Sequence Labeling

Corresponds to "feature detection" for document-level classification models

- Training: $\mathbb{D} = \{(\mathbf{x}_d, Y_d) \mid 1 \leq d \leq |\mathbb{D}|\}$
    - Document of N tokens/words: $\mathbf{x} = x_1, \ldots, x_n, \ldots, x_N$
    - Document-level label: $Y \in \{-1, 1\}$
- Inference:
    - Predict token-level labels: $\hat{\mathbf{y}} = \hat{y}_1, \ldots, \hat{y}_n, \ldots, \hat{y}_N$, where $\hat{y}_n \in \{-1, 1\}$

Task: ~~Zero-Shot~~ Supervised Binary Sequence Labeling

- Training: $\mathbb{D} = \{(\mathbf{x}_d, \cancel{Y_d}) \mid 1 \leq d \leq |\mathbb{D}|\}$ $\mathbf{y}_d$
  - Document of N tokens/words: $\mathbf{x} = x_1, \ldots, x_n, \ldots, x_N$
  - ~~Document-level label: $Y \in \{-1,1\}$~~

    Token-level labels: $\mathbf{y} = y_1, \ldots, y_n, \ldots, y_N$, **where** $y_n \in \{-1,1\}$
- Inference:
  - Predict token-level labels: $\hat{\mathbf{y}} = \hat{y}_1, \ldots, \hat{y}_n, \ldots, \hat{y}_N$, where $\hat{y}_n \in \{-1,1\}$

Inference task is unchanged. Training signal is different.

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Task: Zero-Shot Binary Sequence Labeling

- Zero-Shot Grammatical Error Detection:

$y_1 = -1 \quad y_2 = 1 \quad y_3 = -1 \quad \ldots$

Sentence 1: `The runing example will be grammatical error detection, predicting whether or not each word has a grammatical error.`

$Y = 1$

Sentence 2: `See the paper for additional datasets and tasks.`

$Y = -1$

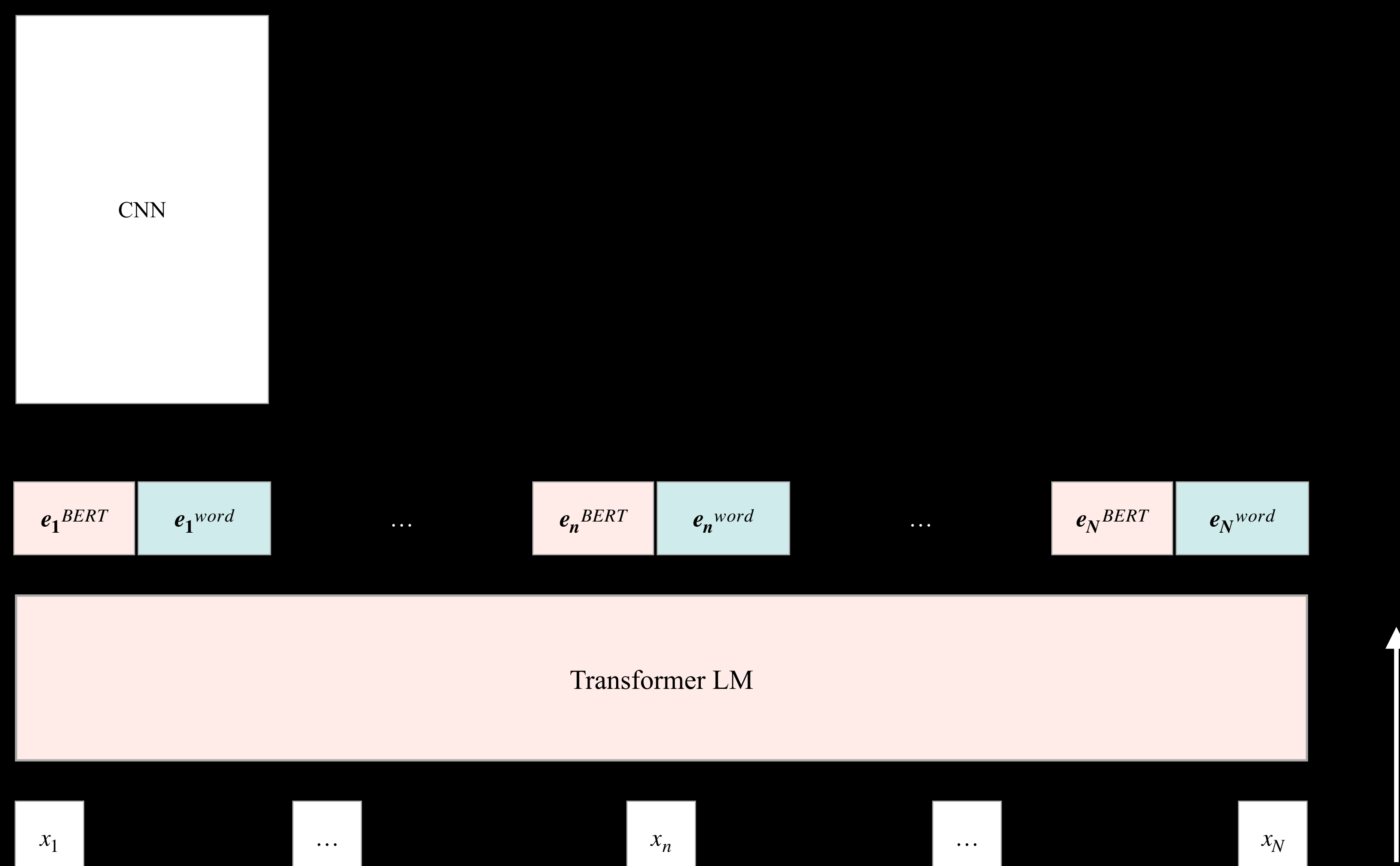
Intrinsic Challenges for Zero-Shot Labeling

- Multiple annotation schemes could be consistent with the document-level label
    - Need to think carefully about the inductive bias
    - Need some facility for adaptability to available priors
- Parameters of the network are not identifiable
    - Will instead aim for *instrospectable and updatable constraints against the observed data*

Mirrors the challenges with neural network interpretability, more generally

Horizontal (across the input) Model Decomposition

$M = 1000$ kernel-width 1 filters



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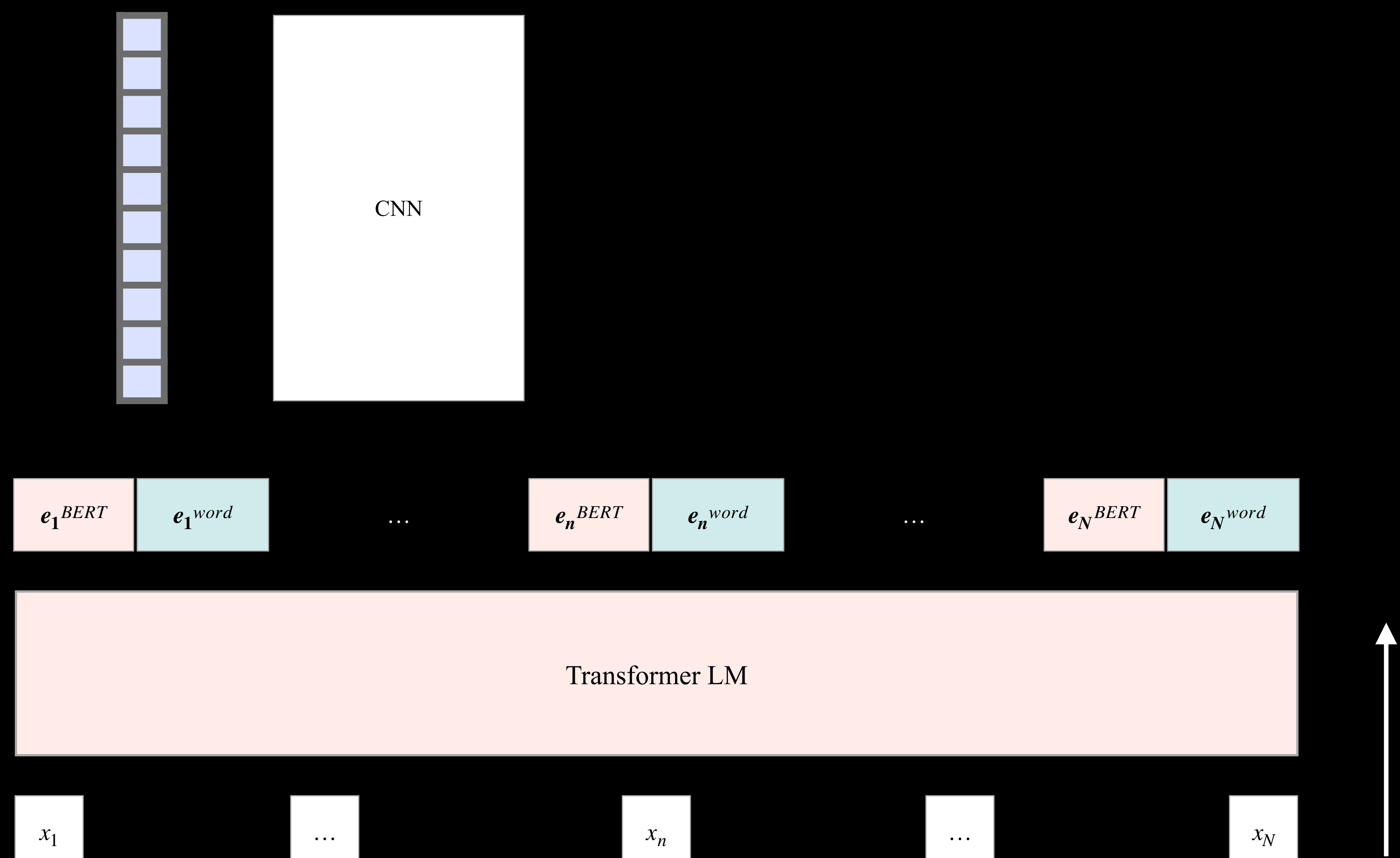

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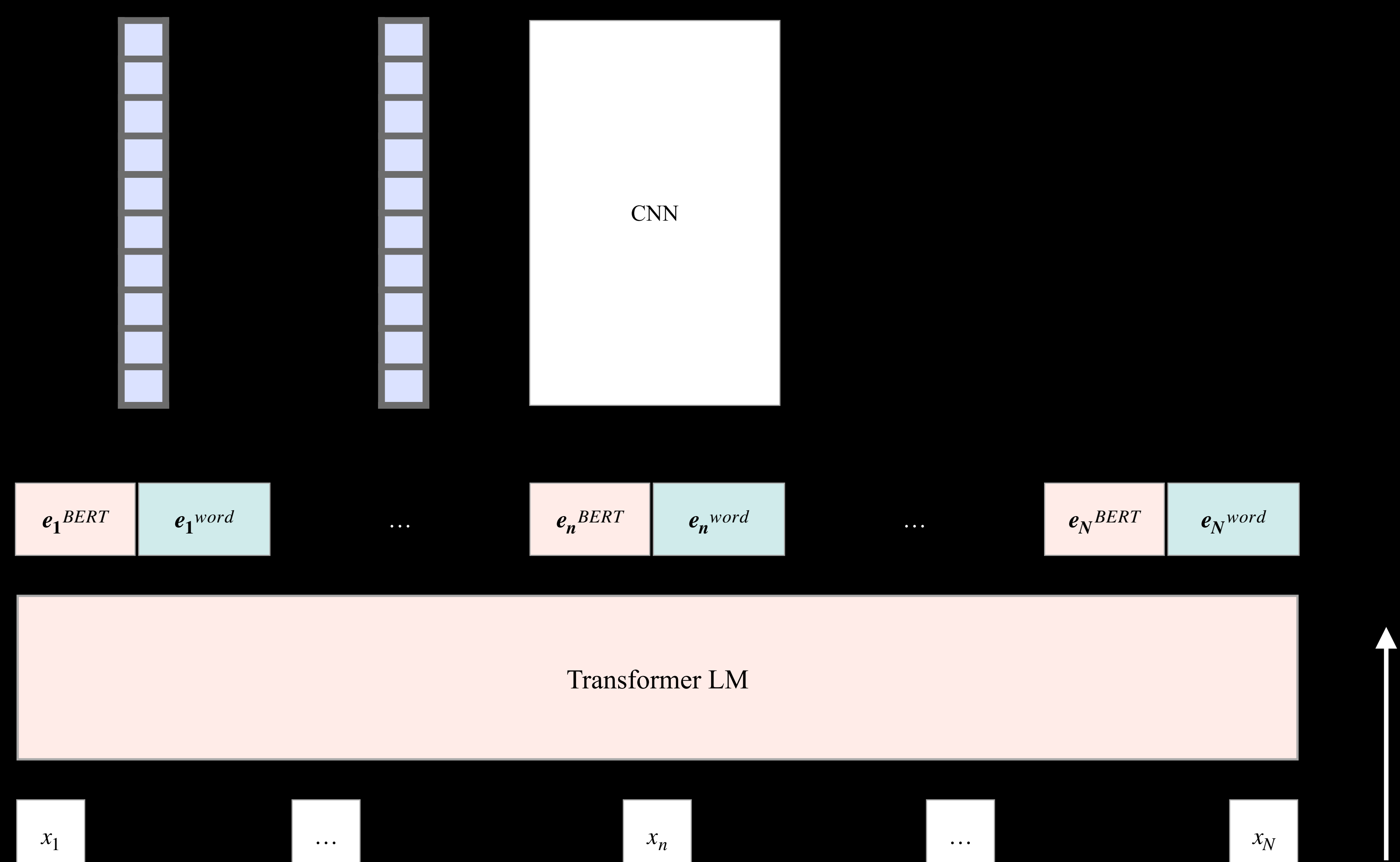

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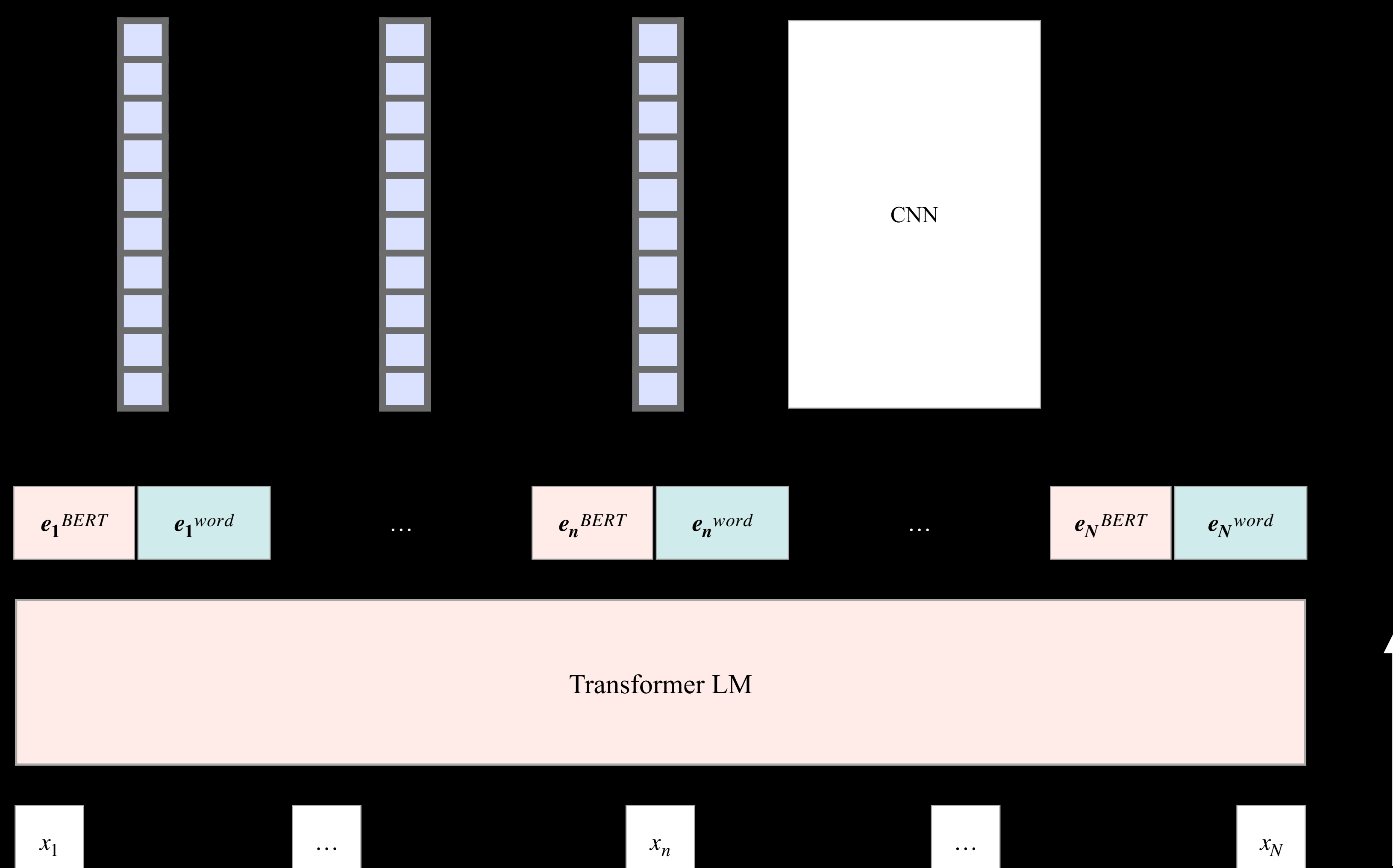

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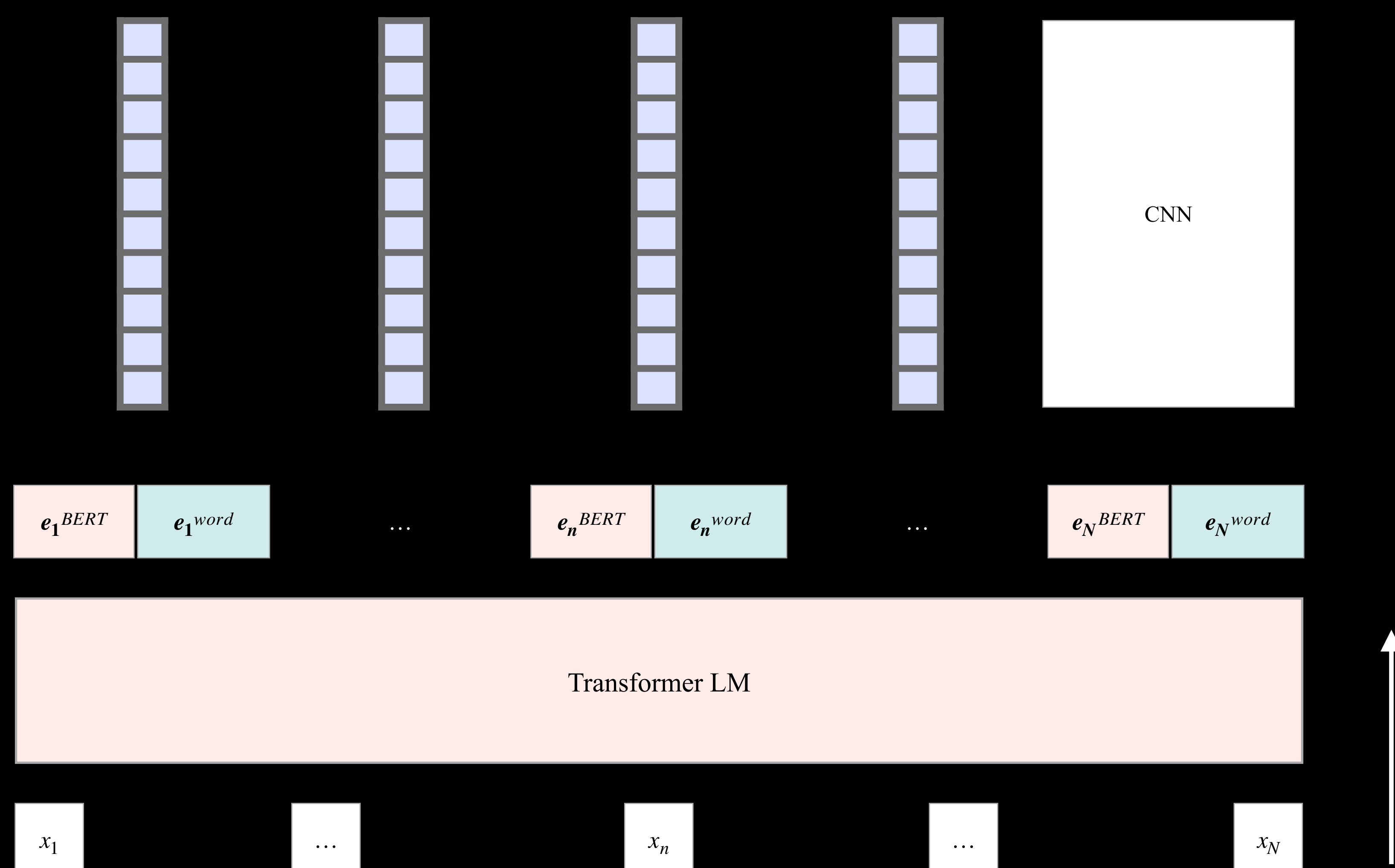

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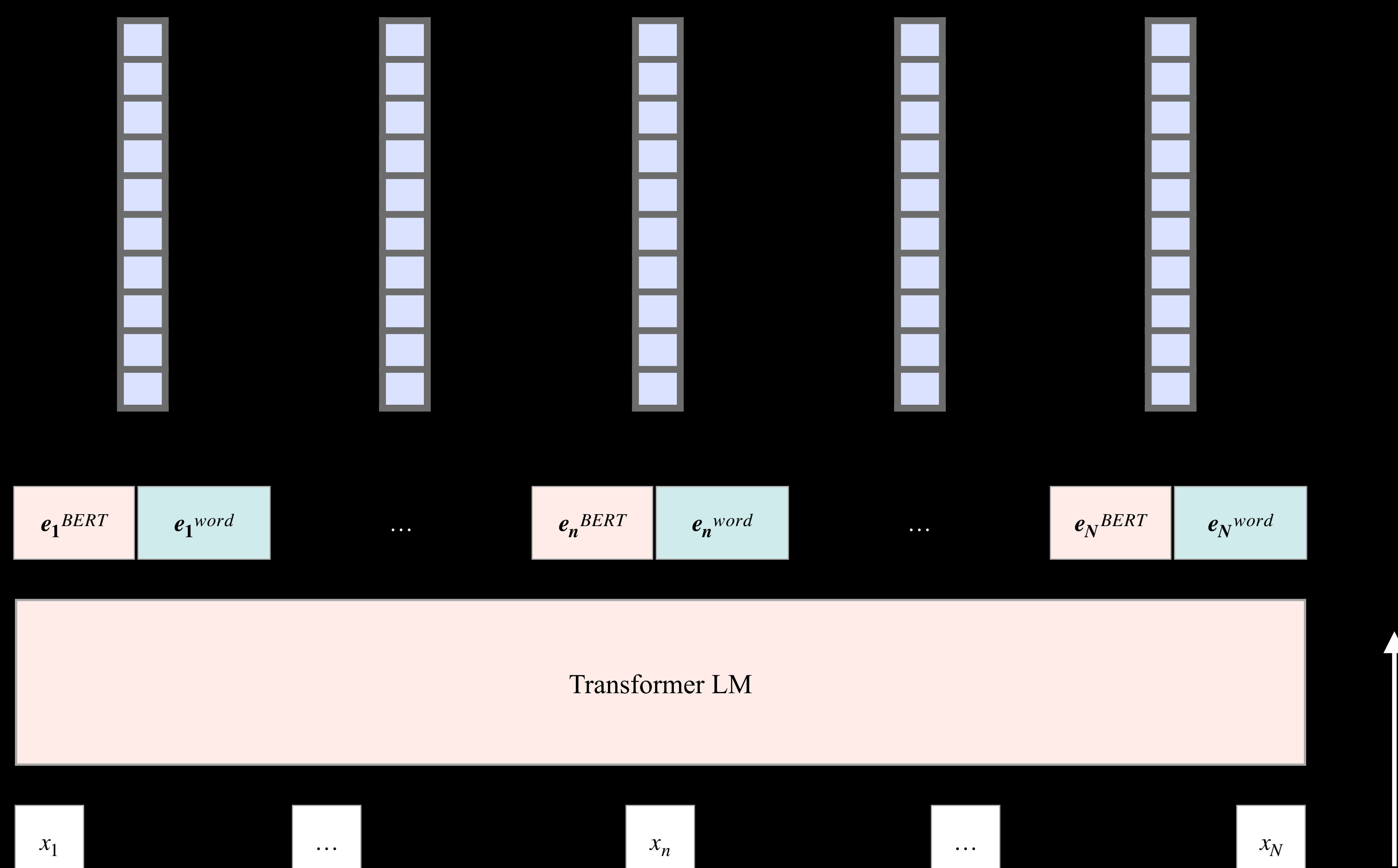

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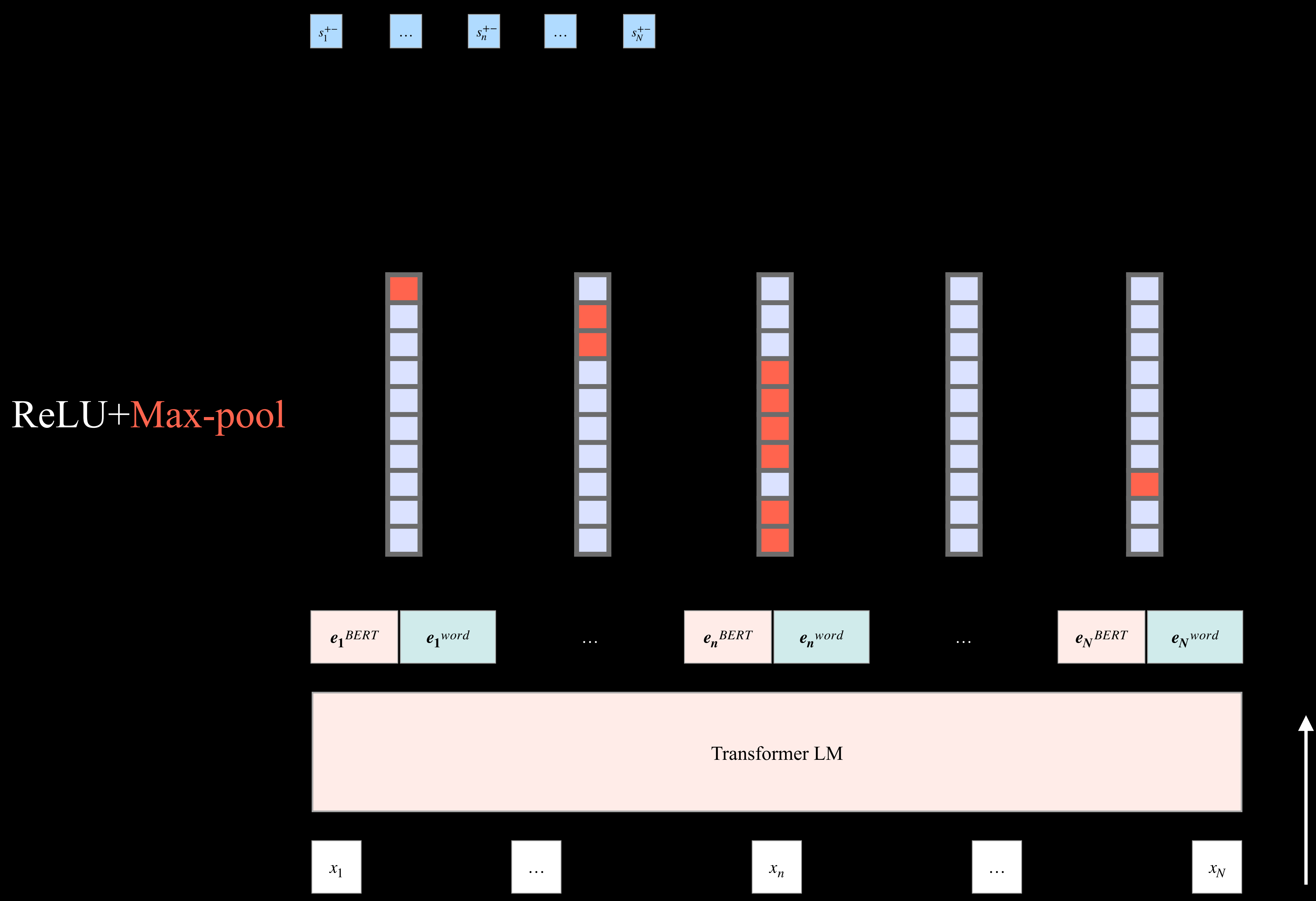

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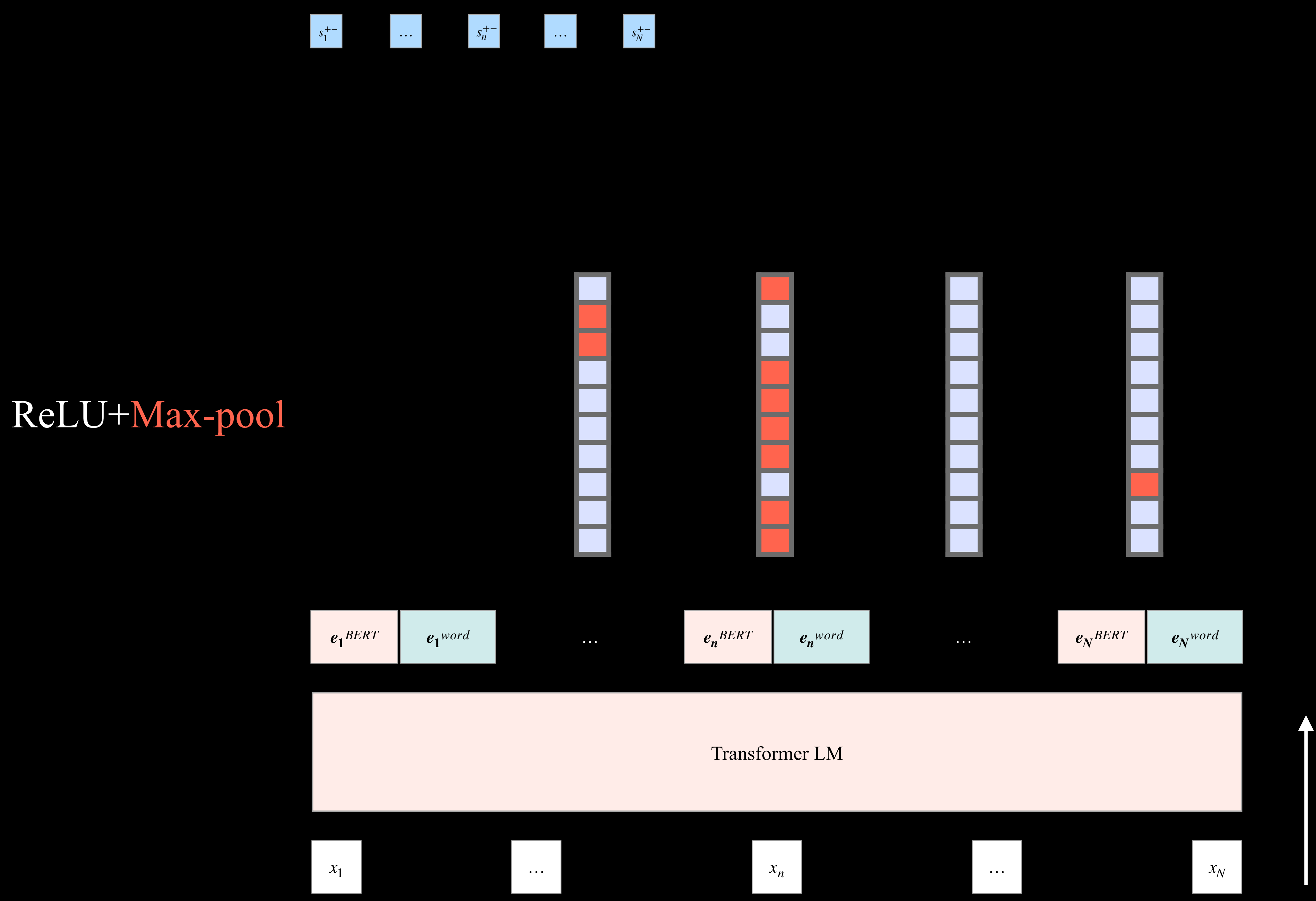

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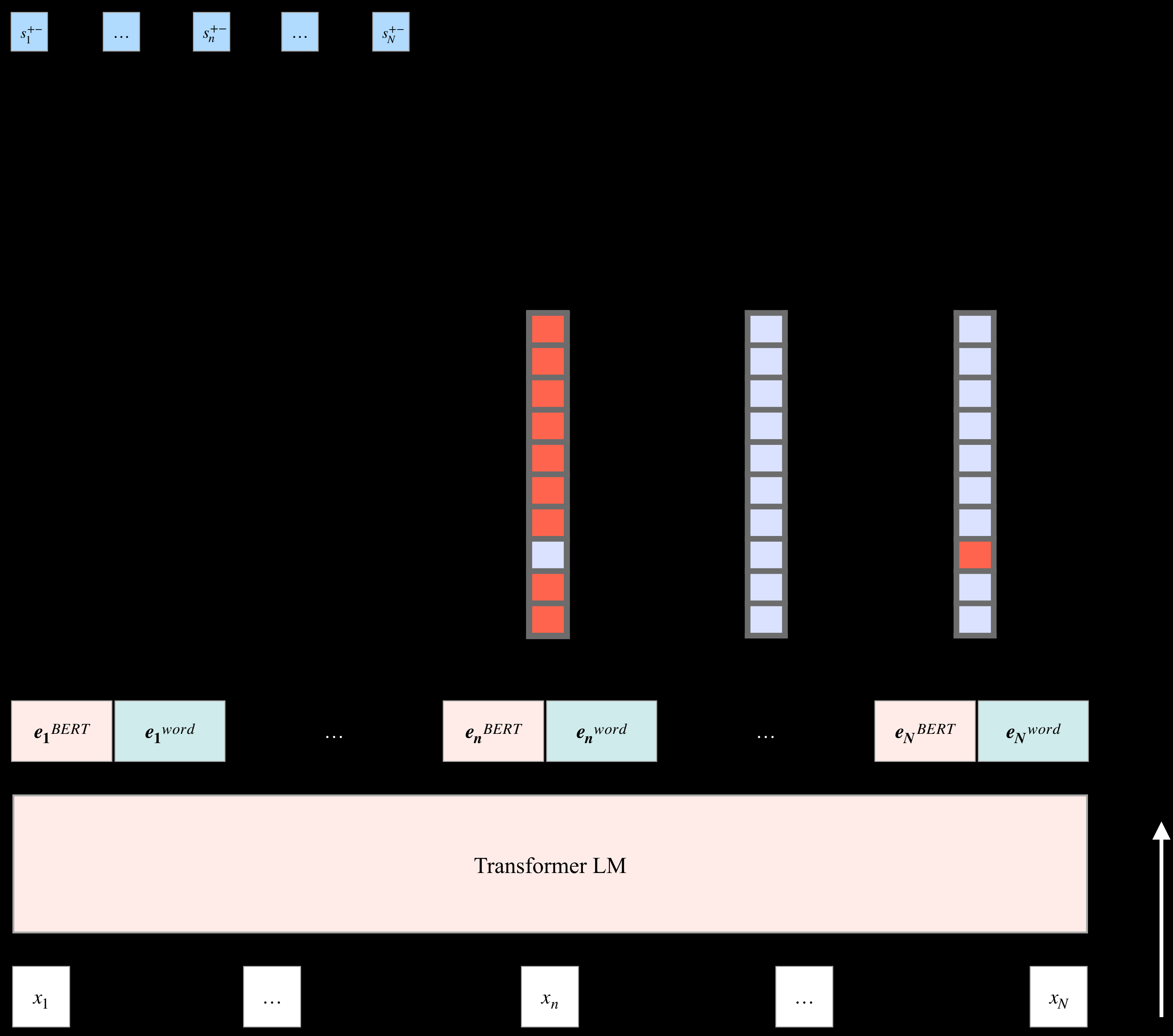
Horizontal (across the input) Model Decomposition

ReLU+Max-pool



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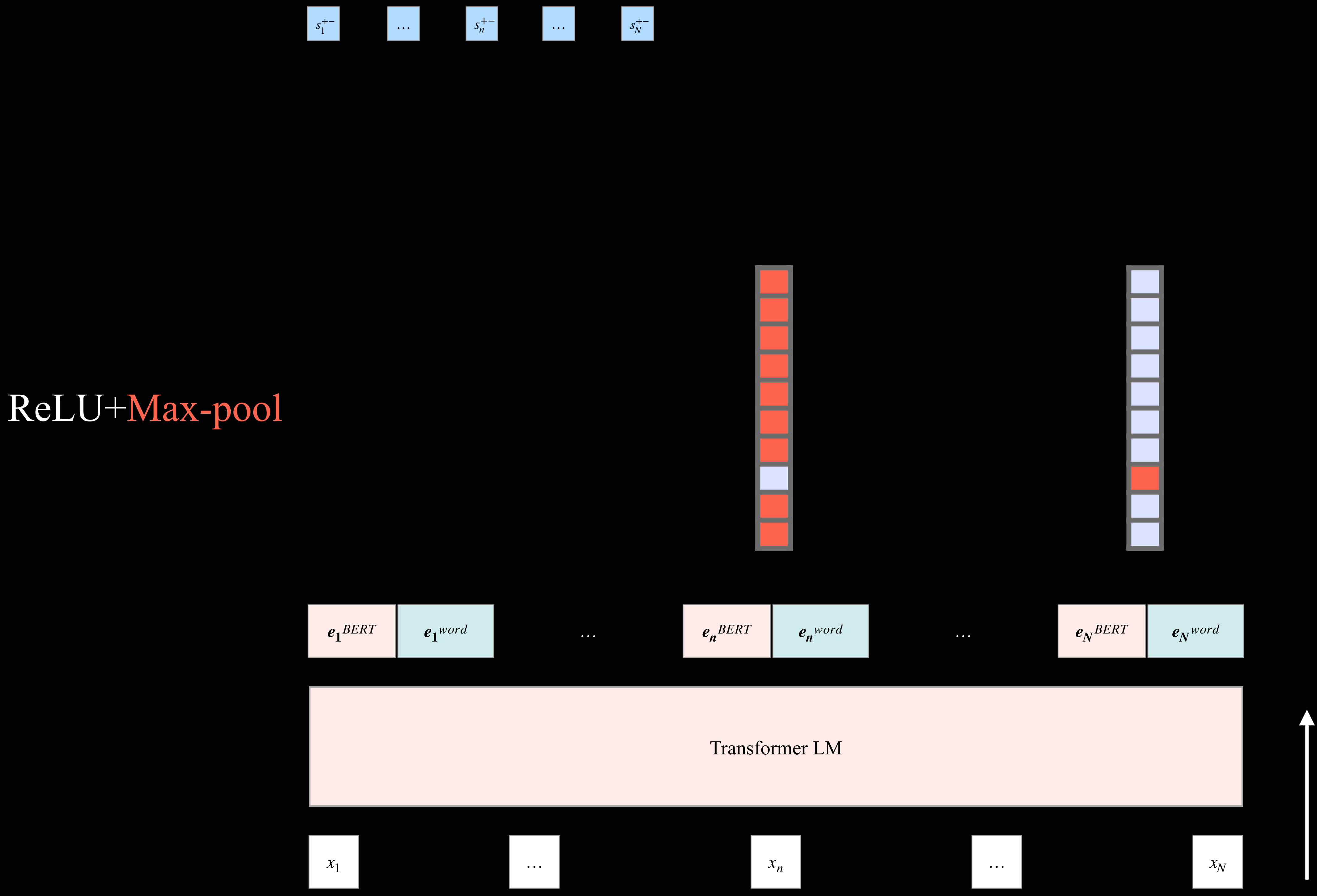

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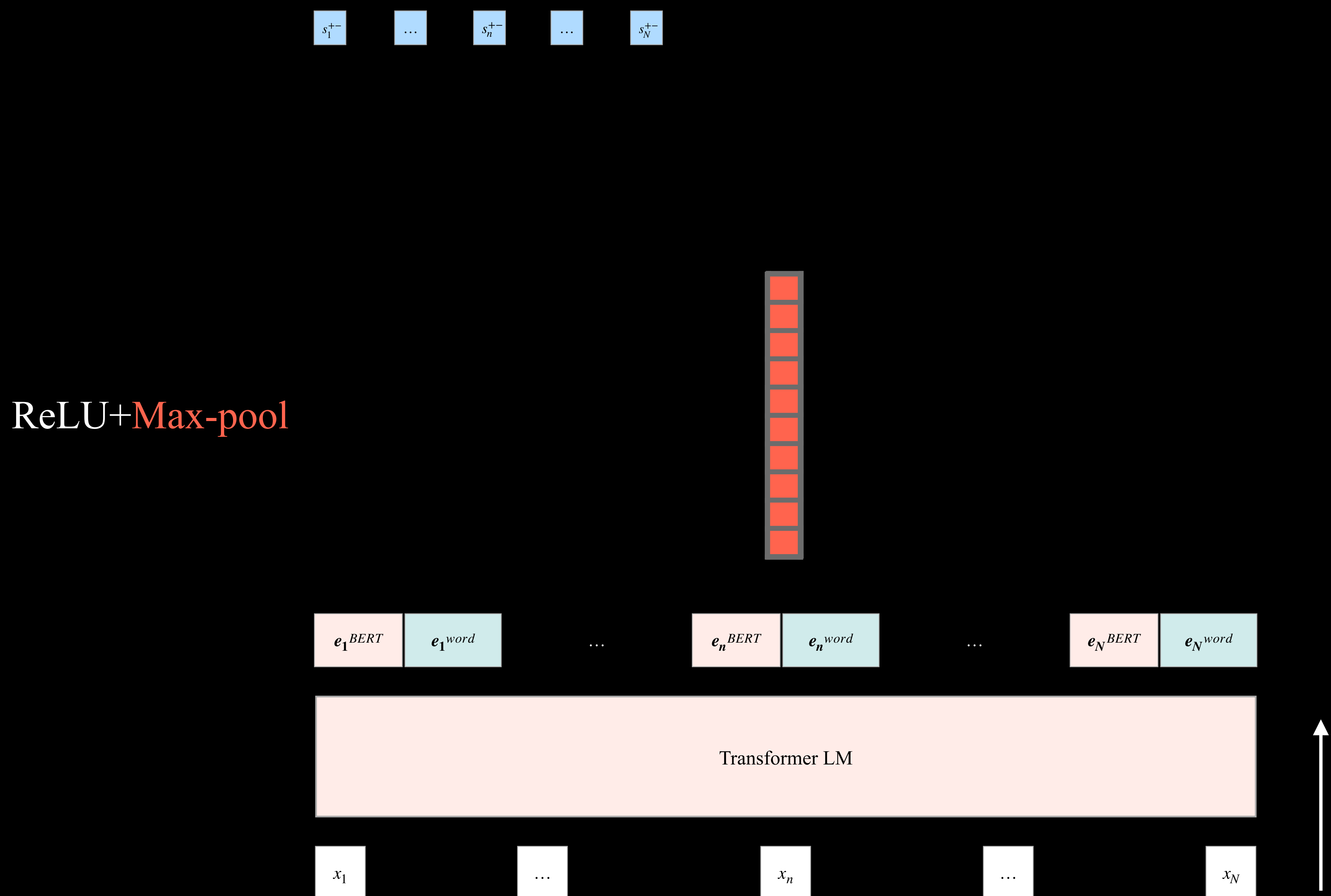

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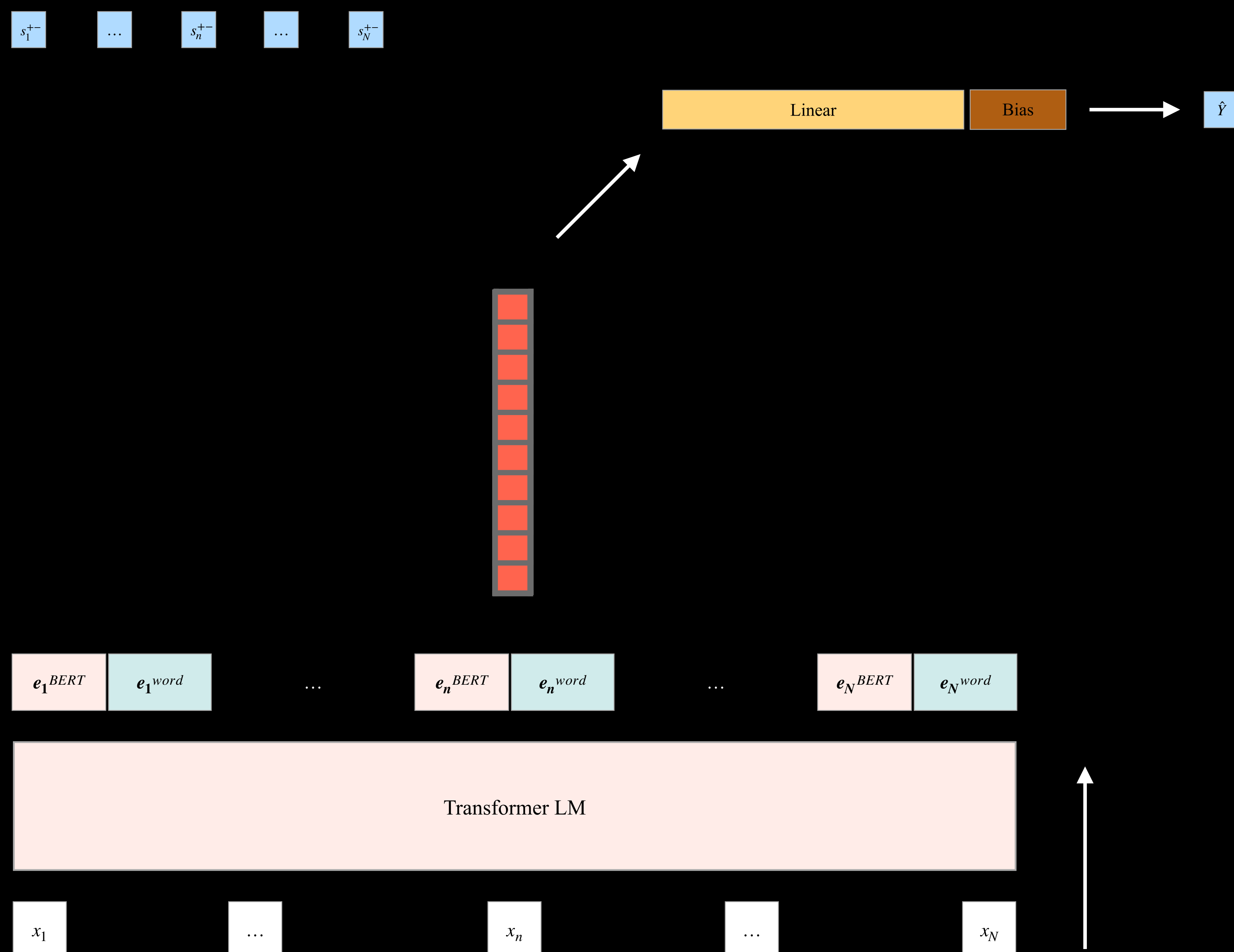

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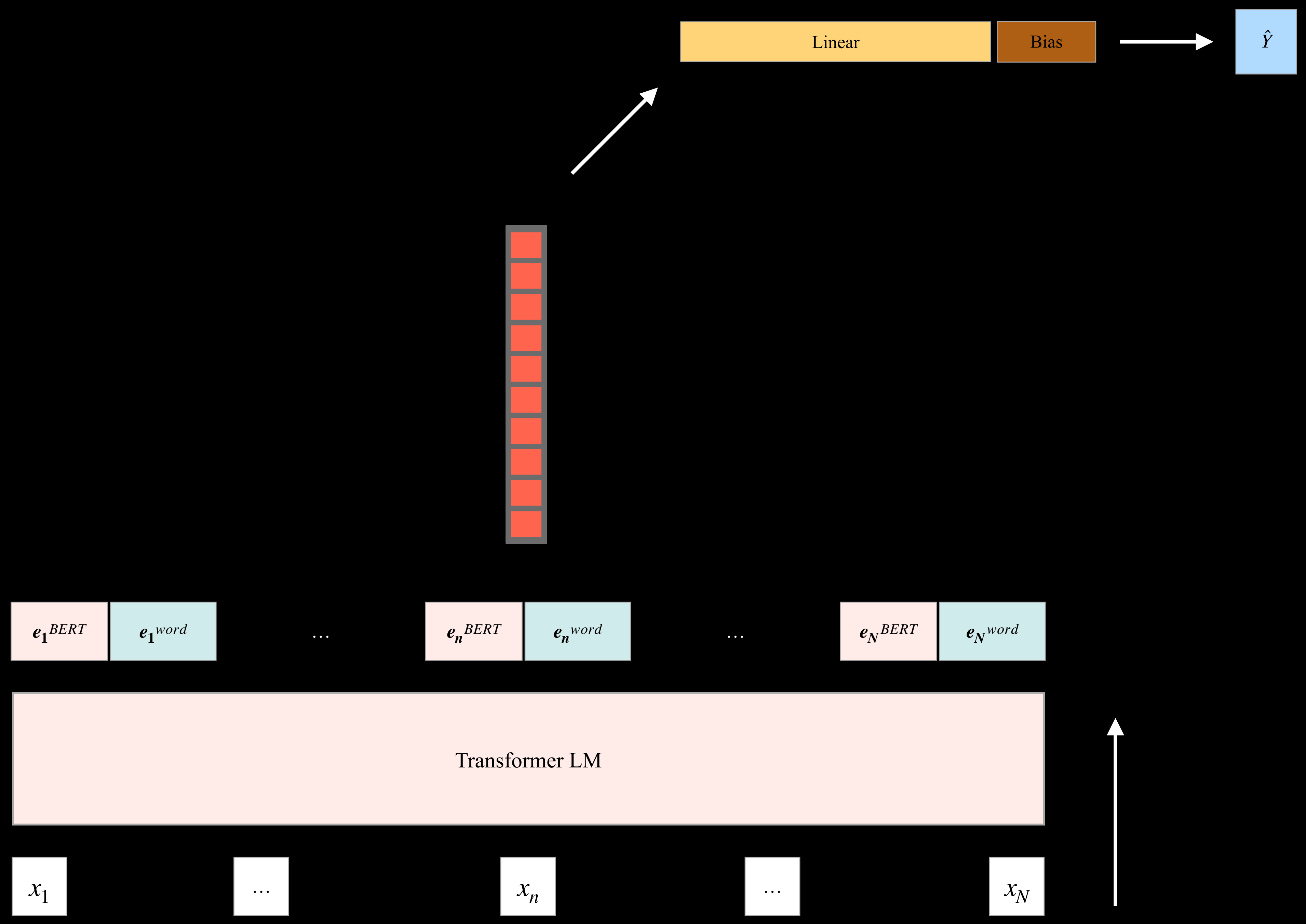

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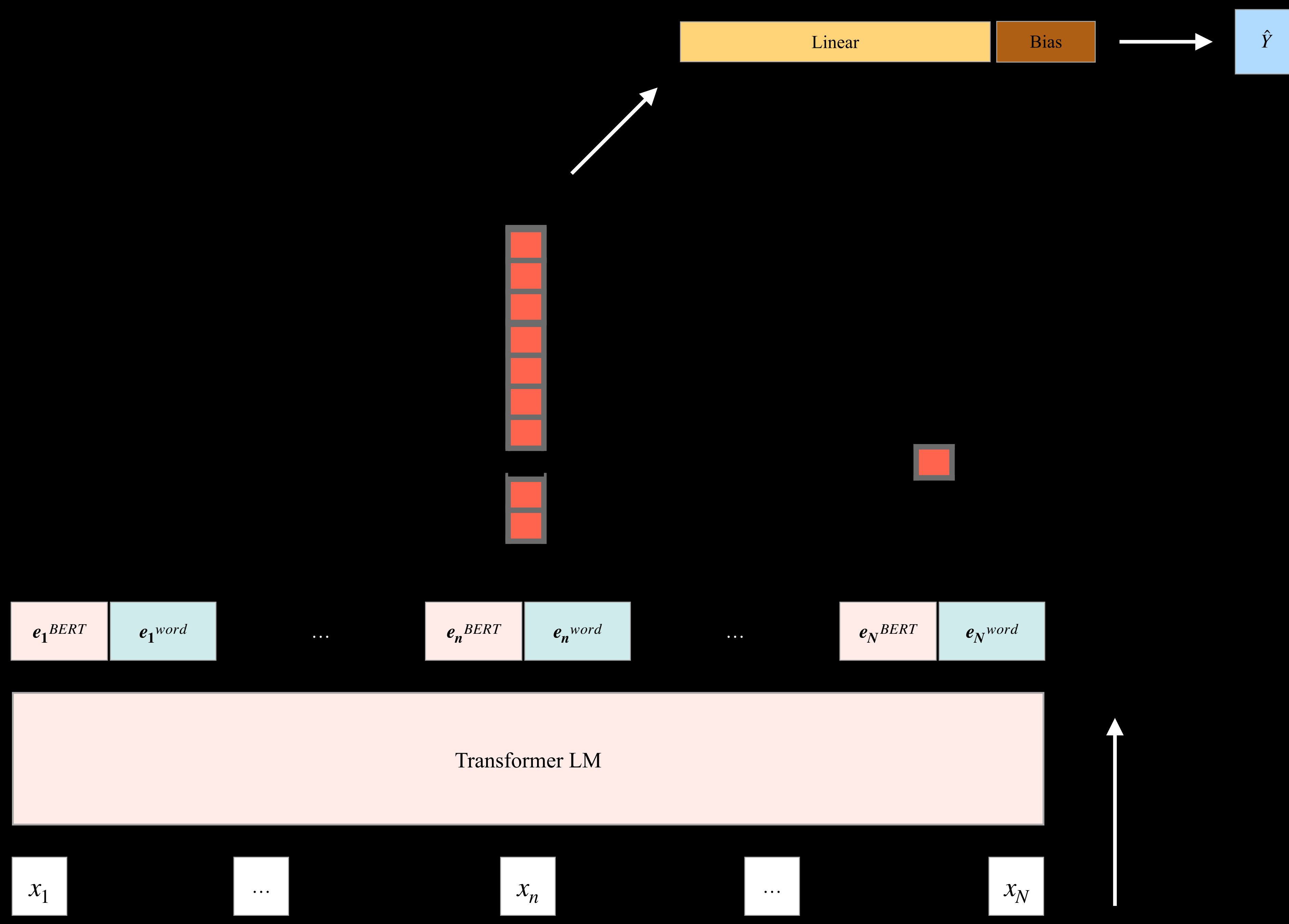

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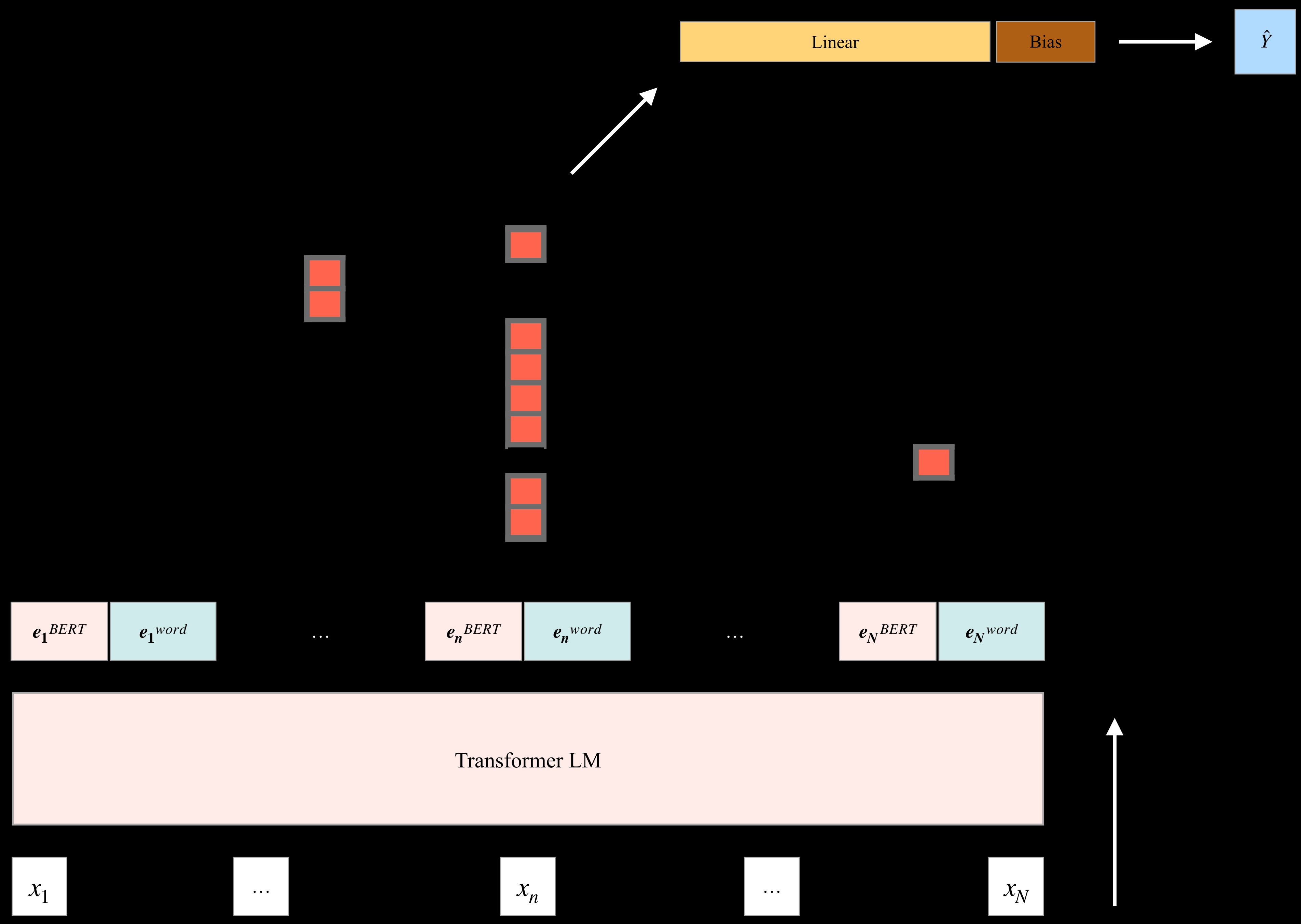

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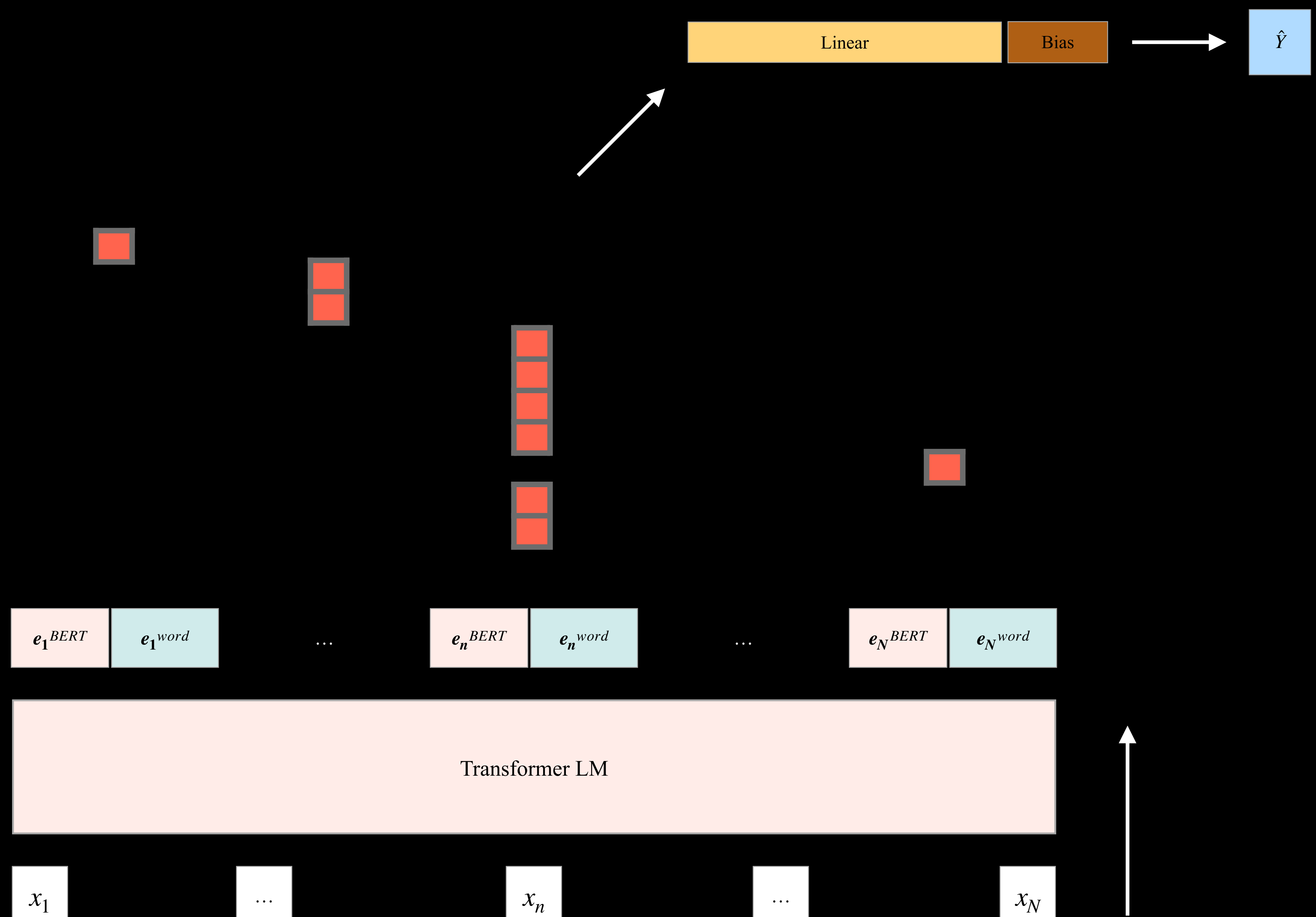

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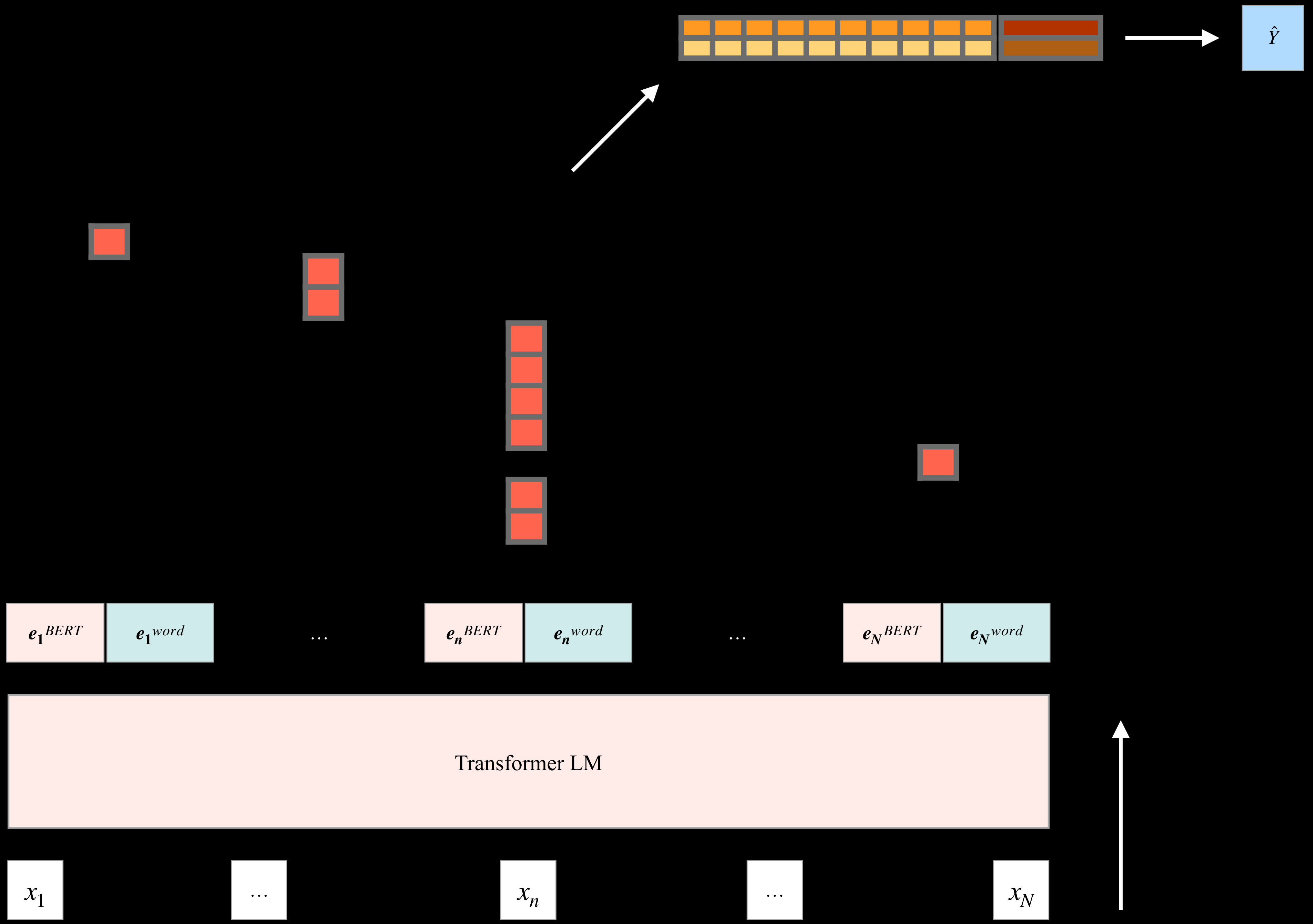

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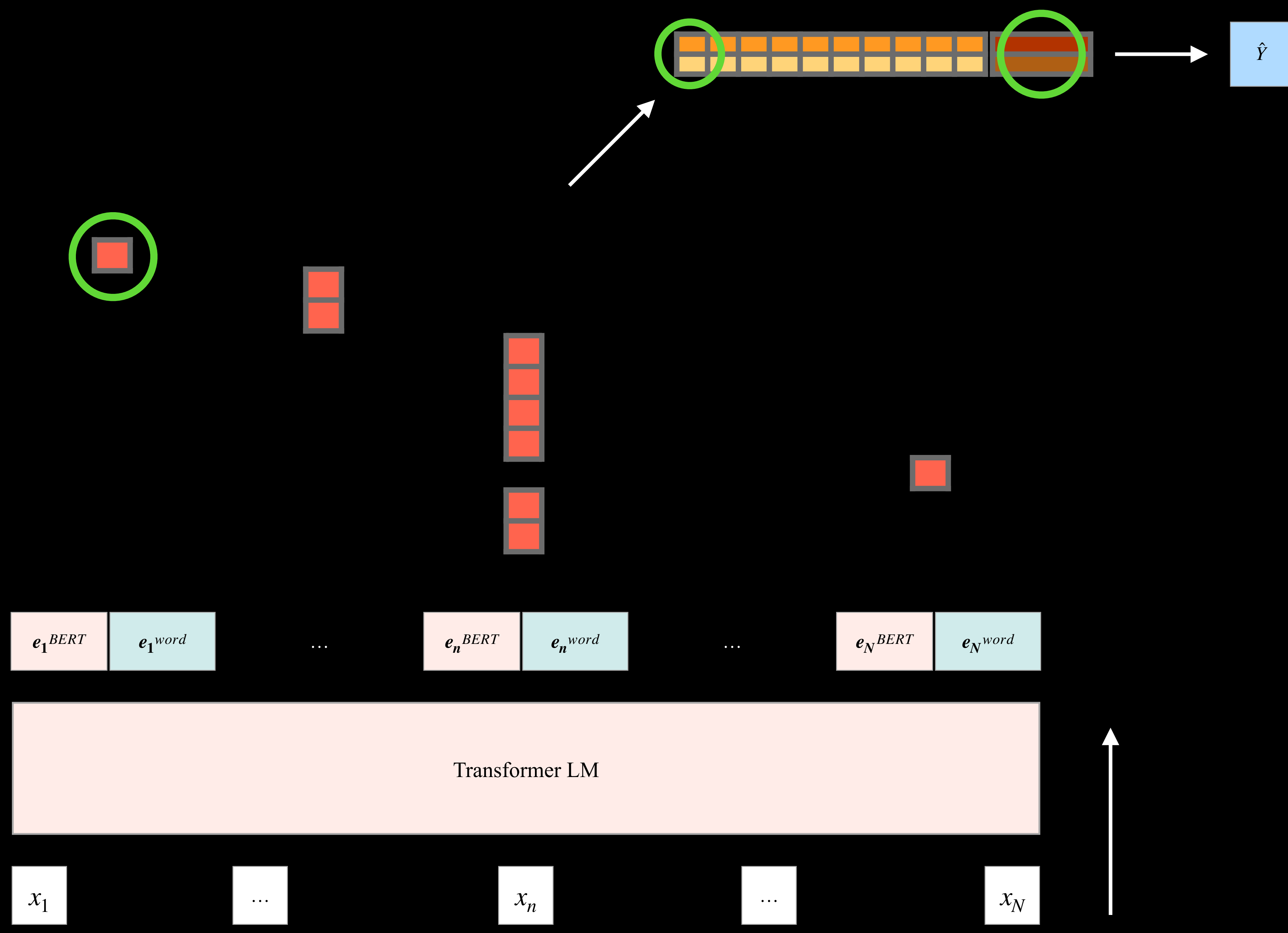

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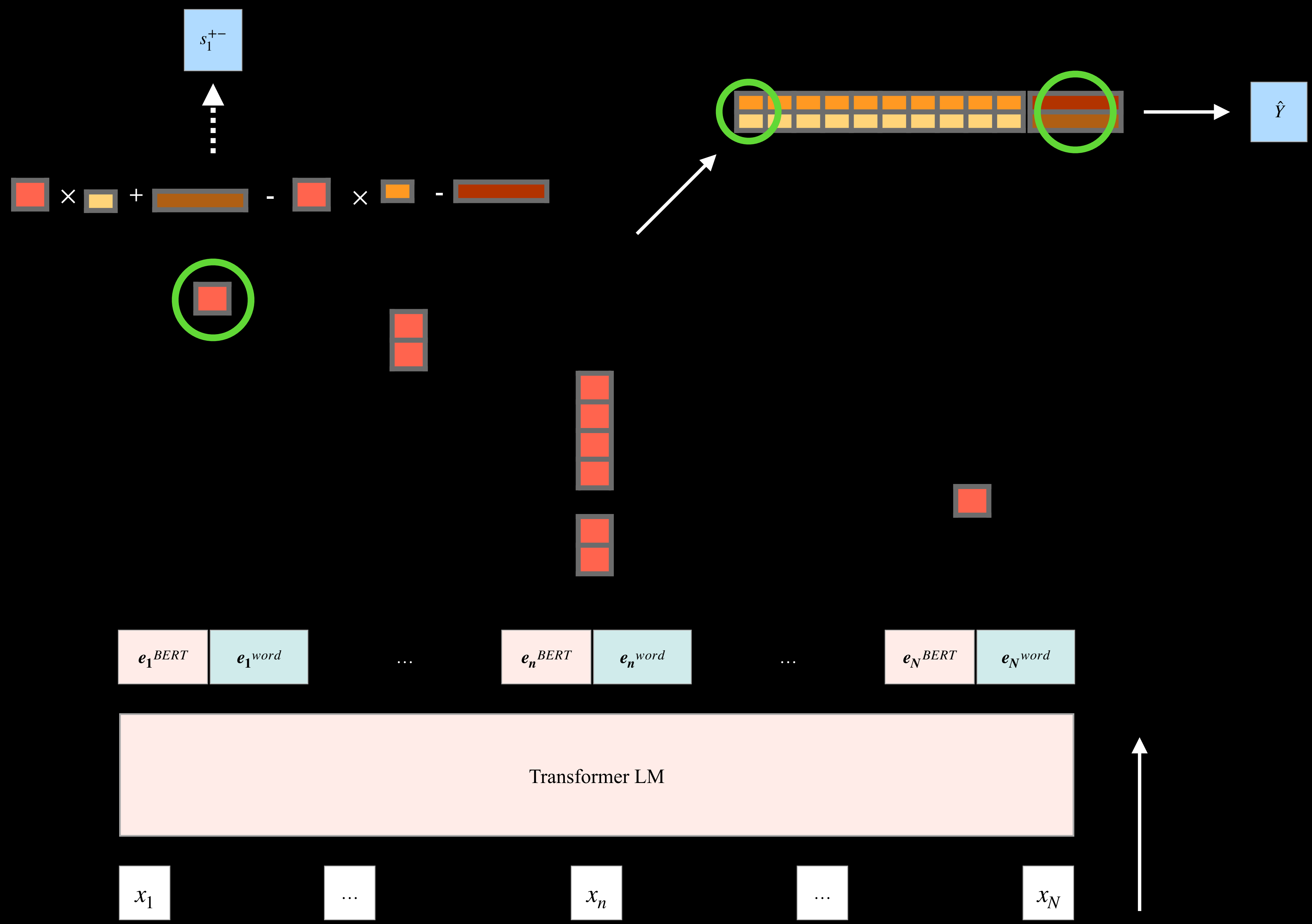

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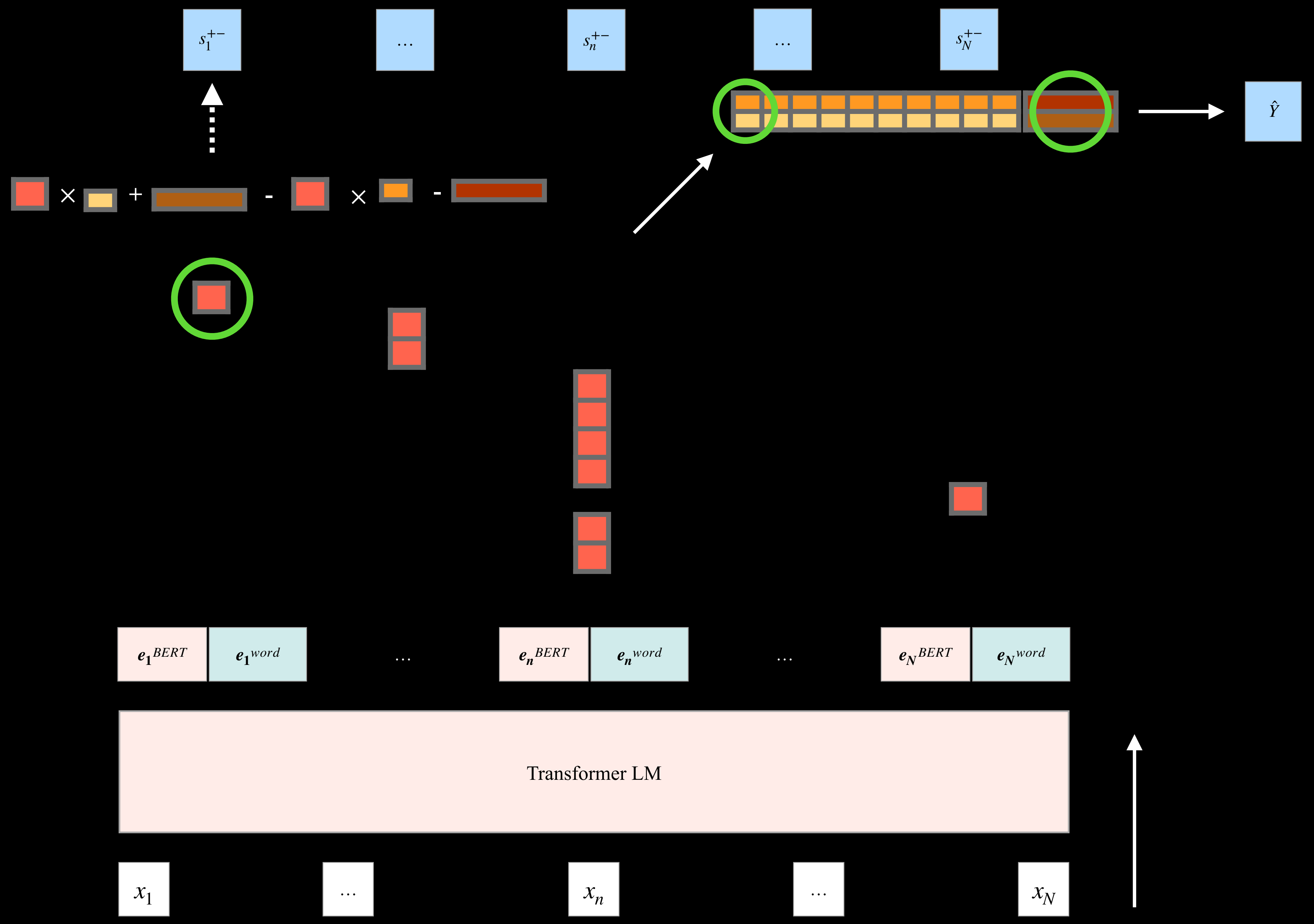

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  - $\mathcal{L}_{min} = -\log(1 - \sigma(s^{+-}_{min}))$
    - $s^{+-}_{min} = \min(s^{+-}_1, \ldots, s^{+-}_n, \ldots, s^{+-}_N)$
  - $\mathcal{L}_{max} = -Y' \cdot \log \sigma(s^{+-}_{max}) - (1 - Y') \cdot \log(1 - \sigma(s^{+-}_{max}))$
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Stronger priors (w.r.t. label distribution)

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Difference practically useful … but also concerning ($\hat{Y}$ similar)

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- Fully-supervised (token-level)
  - $\mathcal{L}_n = -y'_n \cdot \log \sigma(s^{+-}_n) - (1 - y'_n) \cdot \log(1 - \sigma(s^{+-}_n))$

Stronger priors (w.r.t. label distribution) ⟶

Empirical Results

FCE zero-shot sequence labeling test set results (Appendix: Table E.1)
†Results from previous works

Empirical Results

	Sentence-level	Token-level			
Model	F_1	P	R	F_1	$F_{0.5}$
RANDOM	58.30	15.30	50.07	23.44	17.79
MAJORITYCLASS	80.88	15.20	100	26.39	18.31
LIME (ROBERTA$_{BASE}$ TRANSFORMER) †	84.51	19.06	34.70	24.60	20.95

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Can only label max 2 tokens

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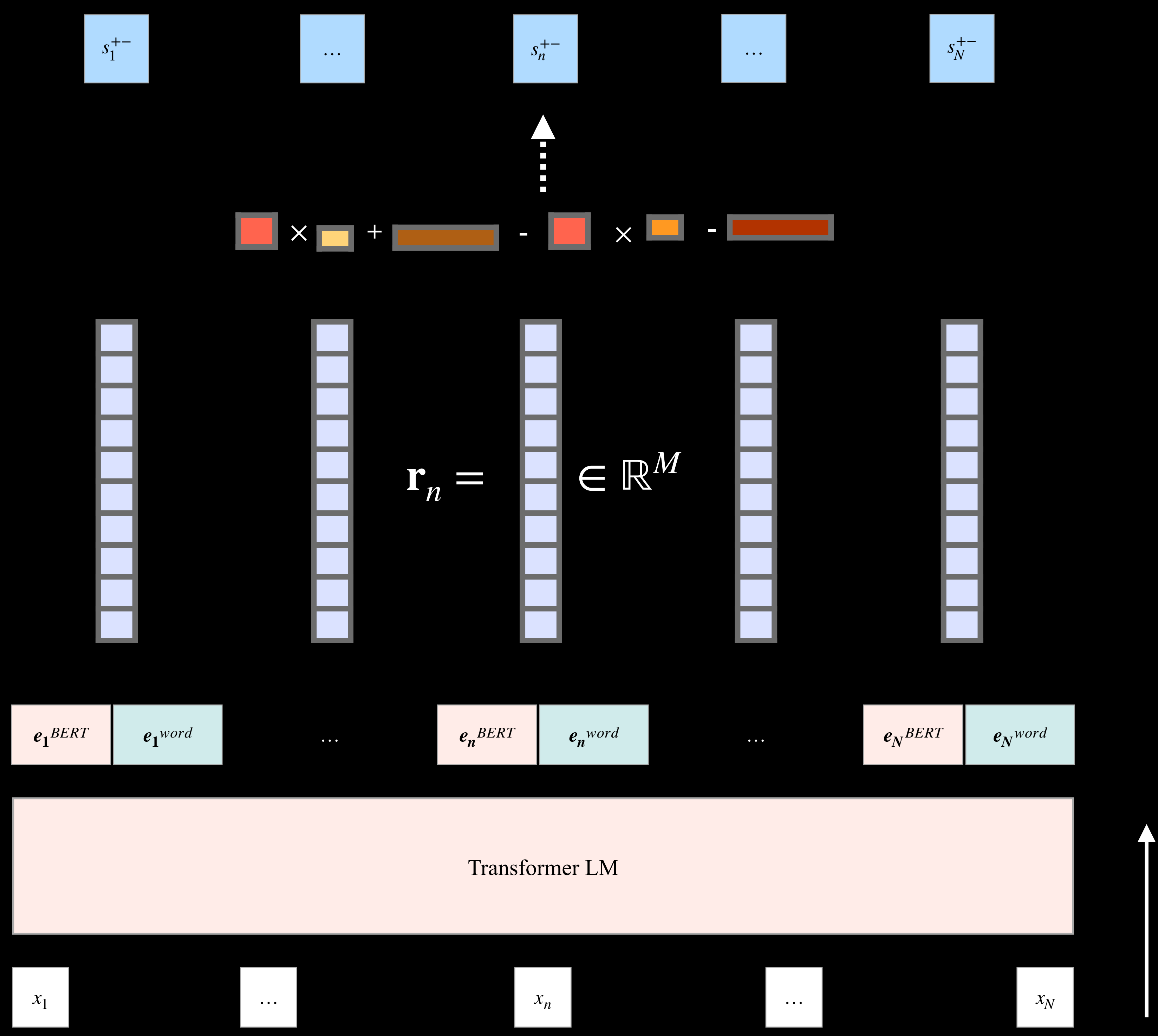
Vertical (across the support set) Model Decomposition via Dense Matching



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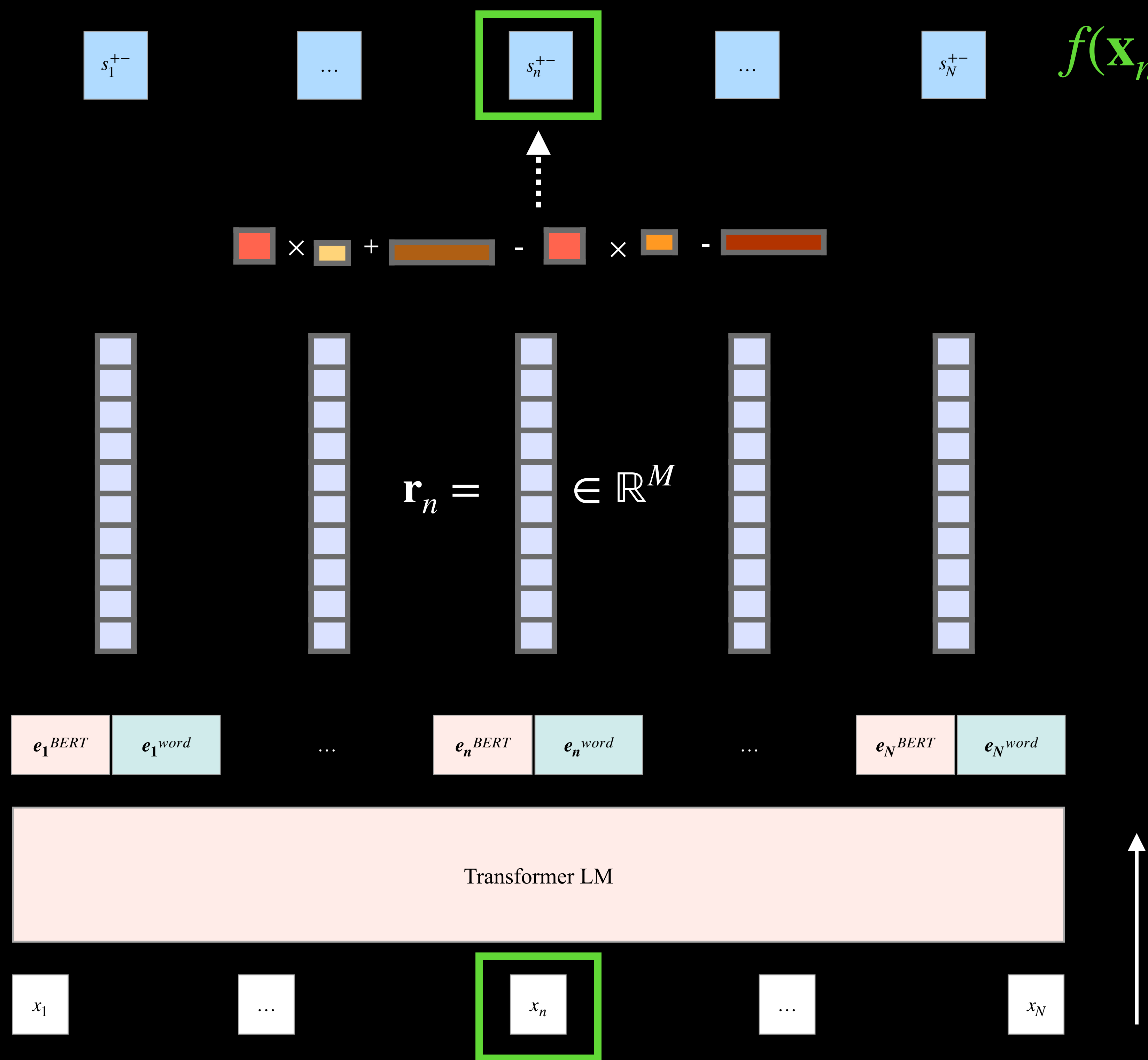
Vertical (across the support set) Model Decomposition via Dense Matching

$f(\mathbf{x}_n) = s_n^{+-}$

$f(\mathbf{x}_n) = u \circ v$



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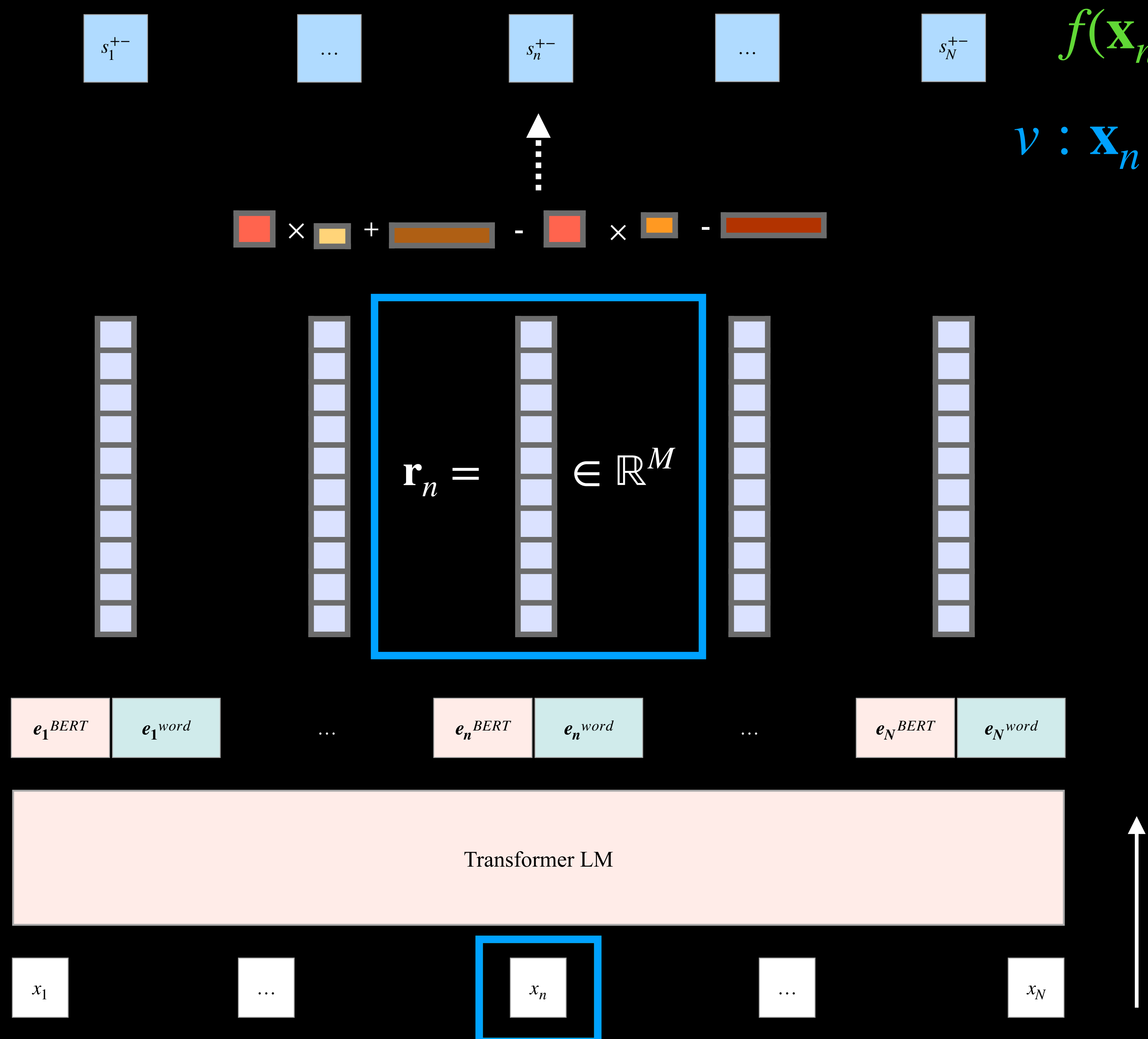
$$v : \mathbf{x}_n \mapsto \mathbf{r}_n \in \mathbb{R}^M$$



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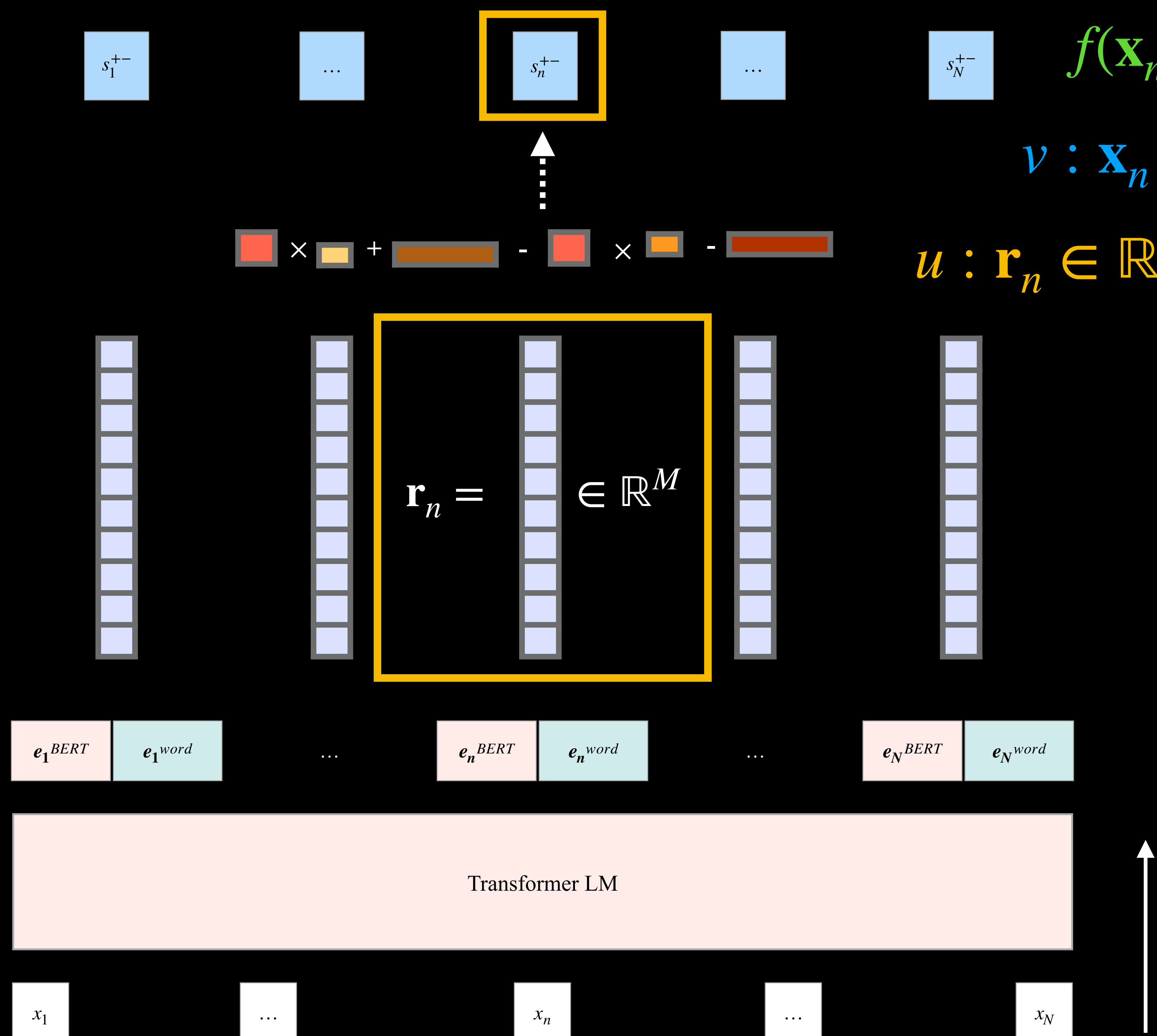
$$f(\mathbf{x}_n) = u \circ v$$

$$v : \mathbf{x}_n \mapsto \mathbf{r}_n \in \mathbb{R}^M$$

$$u : \mathbf{r}_n \in \mathbb{R}^M \mapsto s_n^{+-} \in \mathbb{R}$$



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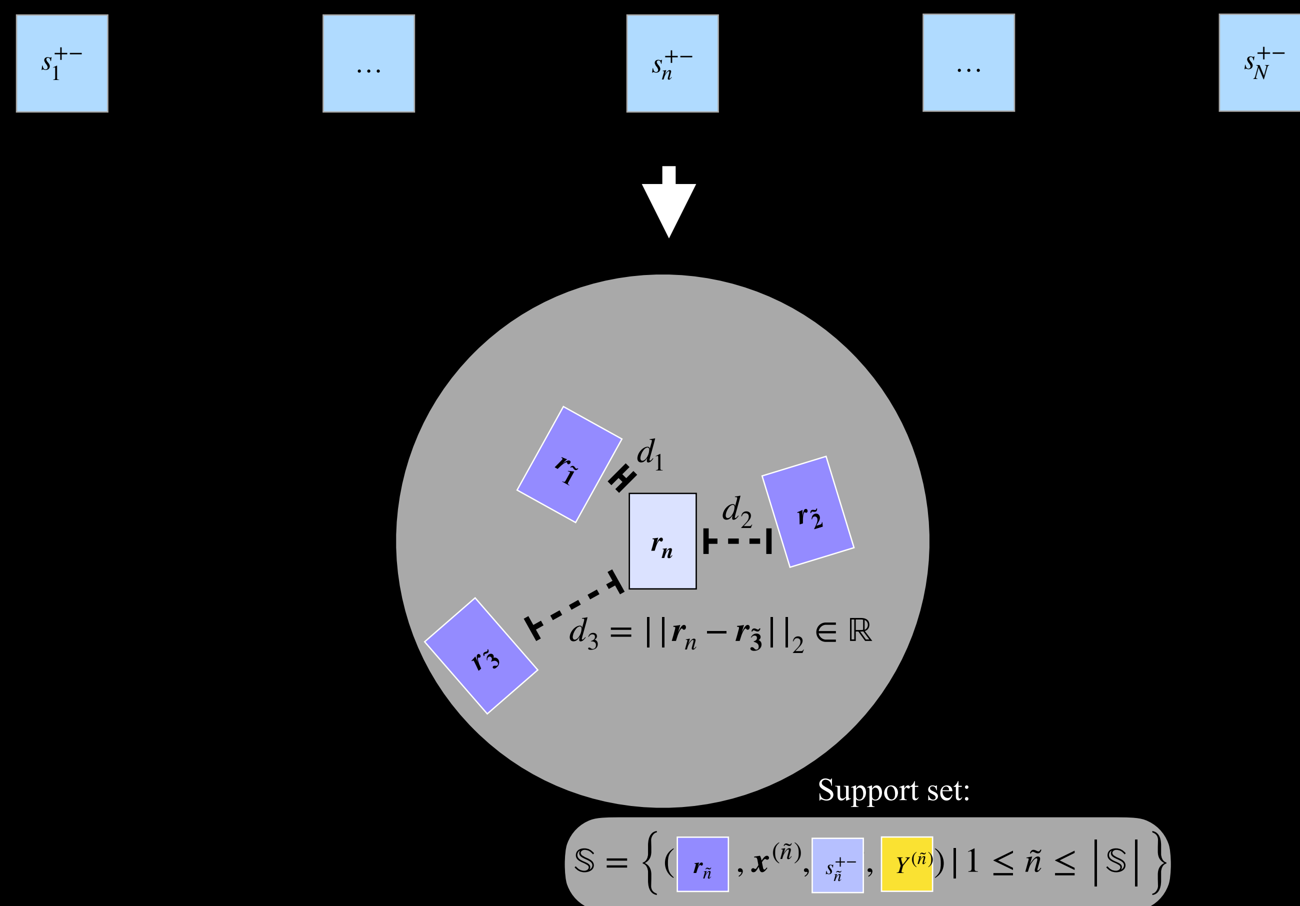

$$
\begin{aligned}
s_n^{+-} \approx \beta &+ w_1 \cdot \left(\tanh(s_{\tilde 1}^{+-}) + \gamma \cdot Y^{(\tilde 1)}\right) \\
&+ w_2 \cdot \left(\tanh(s_{\tilde 2}^{+-}) + \gamma \cdot Y^{(\tilde 2)}\right) \\
&+ w_3 \cdot \left(\tanh(s_{\tilde 3}^{+-}) + \gamma \cdot Y^{(\tilde 3)}\right)
\end{aligned}
\qquad
w_k = \frac{\exp(-d_k/\tau)}{\sum_{k'=1}^{3} \exp(-d_{k'}/\tau)}
$$

Model Approximation

Original model output
(from decomposition)

$$\hat{y}_n = \text{sgn}\left(\text{f}(\mathbf{x}_\text{n})\right) = \text{sgn}\left(\text{s}_\text{n}^{+-}\right) \approx$$

$y_k \in \{-1,1\}$ if token-level labels are available; otherwise, document-level $Y^{(k)} \in \{-1,1\}$

$$\hat{y}_n^{KNN} = \text{sgn}\left(\text{f}(\mathbf{x}_\text{n})^\text{KNN}\right) = \text{sgn}\left(\beta + \sum_{\text{k} \in \arg \text{K} \min_{\tilde{\text{n}}} ||\mathbf{r}_\text{n} - \mathbf{r}_{\tilde{\text{n}}}||_2} \text{w}_\text{k} \cdot \left(\tanh(\text{s}_\text{k}^{+-}) + \gamma \cdot \text{Y}^{(\text{k})}\right)\right)$$

K-NN Approximation

$$w_k = \frac{\exp\left(-||\mathbf{r}_n - \mathbf{r}_k||_2/\tau\right)}{\sum_{k' \in \arg K \min_{\tilde{n}} ||\mathbf{r}_n - \mathbf{r}_{\tilde{n}}||_2} \exp\left(-||\mathbf{r}_n - \mathbf{r}_{k'}||_2/\tau\right)}$$

Hyper-parameter: K

Learn β, γ, τ: Loss: $\mathcal{L}_n^{KNN} = -\sigma(s_n^{+-}) \cdot \log \sigma\left(f(\mathbf{x}_n)^{KNN}\right) - (1 - \sigma(s_n^{+-})) \cdot \log\left(1 - \sigma\left(f(\mathbf{x}_n)^{KNN}\right)\right)$

Choose epoch that minimizes: $\delta^{KNN} = \sum_{n \in \textbf{dev}} [\text{sgn}\left(\text{s}_\text{n}^{+-}\right) \neq \text{sgn}\left(\text{f}(\mathbf{x}_\text{n})^\text{KNN}\right)]$

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Empirical Results — Closeness of Approximation

Model Approximation	Model Approximation = Original Model	
	Accuracy	$F_{0.5}$
K-NN Approx. of Transformer ($\text{BERT}_{\text{LARGE}}$) + CNNDecomposition+MinMaxLoss	96.5	76.9
K-NN Approx. of Transformer ($\text{BERT}_{\text{LARGE}}$) + CNNDecomposition (Supervised)	97.0	75.9

Original Model
Transformer ($\text{BERT}_{\text{LARGE}}$) + CNNDecomposition+MinMaxLoss
Transformer ($\text{BERT}_{\text{LARGE}}$) + CNNDecomposition (Supervised)

<u>Token-level</u> FCE K-NN held-out dev set results (Main text: Table 4)

Empirical Results — Closeness of Approximation

Model Approximation	Model Approximation = Ground-truth	Model Approximation = Original Model	
	$F_{0.5}$	Accuracy	$F_{0.5}$
K-NN Approx. of Transformer ($BERT_{LARGE}$) + CNNDecomposition+MinMaxLoss	52.9	96.5	76.9
K-NN Approx. of Transformer ($BERT_{LARGE}$) + CNNDecomposition (Supervised)	59.4	97.0	75.9

Original Model	Original Model = Ground-truth
	$F_{0.5}$
Transformer ($BERT_{LARGE}$) + CNNDecomposition+MinMaxLoss	49.6
Transformer ($BERT_{LARGE}$) + CNNDecomposition (Supervised)	59.5

<u>Token-level</u> FCE K-NN held-out dev set results (Main text: Table 4)

Model Approximation: Error Term

$$\hat{y}_n^{KNN} = \mathrm{sgn}\left(\mathrm{f}(\mathbf{x}_\mathrm{n})^{\mathrm{KNN}}\right) = \mathrm{sgn}\left(\beta + \sum_{\mathrm{k} \in \arg \underset{\tilde{\mathrm{n}}}{\mathrm{K}} \min ||\mathbf{r}_\mathrm{n} - \mathbf{r}_{\tilde{\mathrm{n}}}||_2} \mathrm{w}_\mathrm{k} \cdot \left(\tanh(\mathrm{s}_\mathrm{k}^{+-}) + \gamma \cdot \mathrm{Y}^{(\mathrm{k})}\right)\right) \boxed{+\epsilon}$$

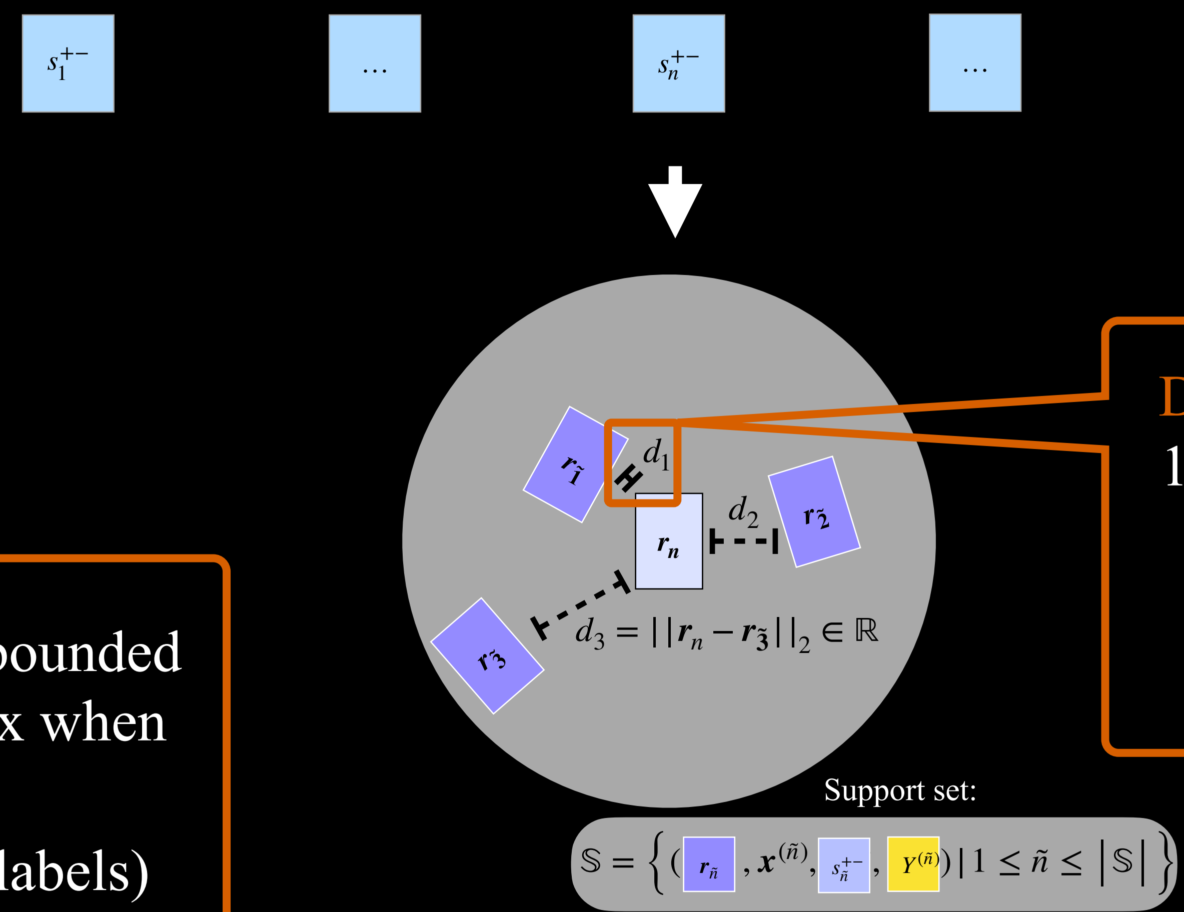
Model Approximation: Error Term

$$\hat{y}_n^{KNN} = \mathrm{sgn}\left(\mathrm{f}(\mathbf{x}_\mathrm{n})^{\mathrm{KNN}}\right) = \mathrm{sgn}\left(\beta + \sum_{\mathrm{k} \in \mathrm{arg}\, \underset{\tilde{\mathrm{n}}}{\mathrm{K}} \min ||\mathbf{r}_\mathrm{n} - \mathbf{r}_{\tilde{\mathrm{n}}}||_2} \mathrm{w}_\mathrm{k} \cdot \left(\tanh(\mathrm{s}_\mathrm{k}^{+-}) + \gamma \cdot \mathrm{Y}^{(\mathrm{k})}\right)\right) \boxed{+\epsilon}$$

Luckily, we can say *a lot* about the errors in practice

Difficult instances to predict also tend to be difficult instances over which to approximate the model.

Leveraging Model Approximations for Prediction Reliability Heuristics & Screening Input Dissimilar to the Support Set

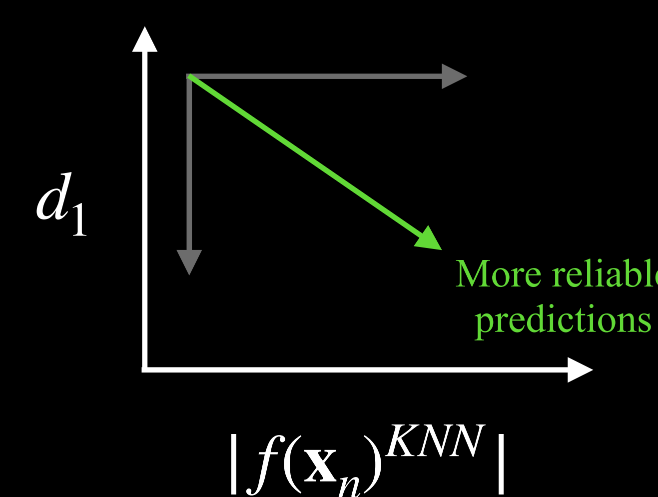


Data uncertainty: Distance to 1st match (d_1), an exogenous factor, captures uncertainty w.r.t. data (training data compared to test data).

Model uncertainty: This bounded value reaches its min/max when $\tanh(s_k^{+-})$ & $Y^{(k)}$ (or y_k, with token-level labels) agree, for all k (assuming $\gamma > 0$).

$$
\begin{aligned}
s_n^{+-} \approx \beta &+ w_1 \cdot \left(\tanh(s_{\tilde 1}^{+-}) + \gamma \cdot Y^{(\tilde 1)}\right) \\
&+ w_2 \cdot \left(\tanh(s_{\tilde 2}^{+-}) + \gamma \cdot Y^{(\tilde 2)}\right) \\
&+ w_3 \cdot \left(\tanh(s_{\tilde 3}^{+-}) + \gamma \cdot Y^{(\tilde 3)}\right)
\end{aligned}
$$

$$
w_k = \frac{\exp(-d_k/\tau)}{\sum_{k'=1}^{3} \exp(-d_{k'}/\tau)}
$$



Magnitude of the K-NN Output

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OOD/Domain-shifted Task Variant

- Add already correct data (NEWS text) to student essay data
    - Distribution of non-errors & language different than training
    - False positive problem
- Analyze ability to detect OOD data & update model (via support set)

Empirical Results—OOD/Domain-Shifted

Model:
K-NN Approx. of Transformer (BERT$_{LARGE}$) +CNNDecomposition+MinMaxLoss

	L^2 distance max constraint	K-NN Output min threshold	Admitted	
$F_{0.5}$	(Class -1, Class 1)	(Class -1, Class 1)	n	n/N
27.0			92597	1.0

Token-level FCE+News2k (domain-shifted) test set results (Main text: Table 6)

Empirical Results—OOD/Domain-Shifted

Model:
K-NN APPROX. OF TRANSFORMER ($\text{BERT}_{\text{LARGE}}$) +CNNDECOMPOSITION+MINMAXLOSS

$F_{0.5}$	L^2 distance max constraint (Class -1, Class 1)	K-NN Output min threshold (Class -1, Class 1)	Admitted n	n/N
27.0			92597	1.0
45.9		(-1.2, 0.8)	38110	0.41
53.5	(34.2, 53.3)		7879	0.09
75.8	(34.2, 53.3)	(-1.2, 0.8)	4180	0.05

Token-level FCE+News2k (domain-shifted) test set results (Main text: Table 6)

Model Approximation: Updatability

$$\hat{y}_n^{KNN} = \mathrm{sgn}\left(\mathrm{f}(\mathbf{x}_\mathrm{n})^{\mathrm{KNN}}\right) = \mathrm{sgn}\left(\beta + \sum_{\mathrm{k} \in \arg \underset{\tilde{\mathrm{n}}}{\mathrm{K}} \min ||\mathbf{r}_\mathrm{n} - \mathbf{r}_{\tilde{\mathrm{n}}}||_2} \mathrm{w}_\mathrm{k} \cdot \left(\tanh(\mathrm{s}_\mathrm{k}^{+-}) + \gamma \cdot \mathrm{Y}^{(\mathrm{k})}\right)\right)$$

Update Support set (representations, labels, meta data)

$$\mathbb{S} = \left\{ \left(\boxed{\boldsymbol{r}_{\tilde{n}}}, \boldsymbol{x}^{(\tilde{n})}, \boxed{s_{\tilde{n}}^{+-}}, \boxed{Y^{(\tilde{n})}} \right) \mid 1 \leq \tilde{n} \leq \left| \mathbb{S} \right| \right\}$$

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Model Approximation: Updatability

$$\hat{y}_n^{KNN} = \mathrm{sgn}\left(\mathrm{f}(\mathbf{x}_\mathrm{n})^{\mathrm{KNN}}\right) = \mathrm{sgn}\left(\beta + \sum_{\mathrm{k} \in \arg \mathrm{K} \min_{\tilde{\mathrm{n}}} ||\mathbf{r}_\mathrm{n} - \mathbf{r}_{\tilde{\mathrm{n}}}||_2} \mathrm{w}_\mathrm{k} \cdot \left(\tanh(\mathrm{s}_\mathrm{k}^{+-}) + \gamma \cdot \mathrm{Y}^{(\mathrm{k})}\right)\right)$$

Update Support set (representations, labels, meta data)

Support set can be viewed as an updatable database

$$\mathbb{S} = \left\{ \left(\boldsymbol{r}_{\tilde{n}}, \boldsymbol{x}^{(\tilde{n})}, s_{\tilde{n}}^{+-}, Y^{(\tilde{n})} \right) \,\middle|\, 1 \le \tilde{n} \le \left|\mathbb{S}\right| \right\}$$

Empirical Results—OOD/Domain-Shift Updatability

Model:
K-NN Approx. of Transformer ($\text{BERT}_{\text{LARGE}}$) +CNNDecomposition+MinMaxLoss

Model	Training set	Support set	$F_{0.5}$
K-NN Approx.	FCE	FCE	27.0
K-NN Approx.	FCE	FCE+OOD	46.3

Original training set

+50k News data

Token-level FCE+News2k (domain-shifted) test set results (Main text: Table 5)

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Empirical Results—OOD/Domain-Shift Updatability

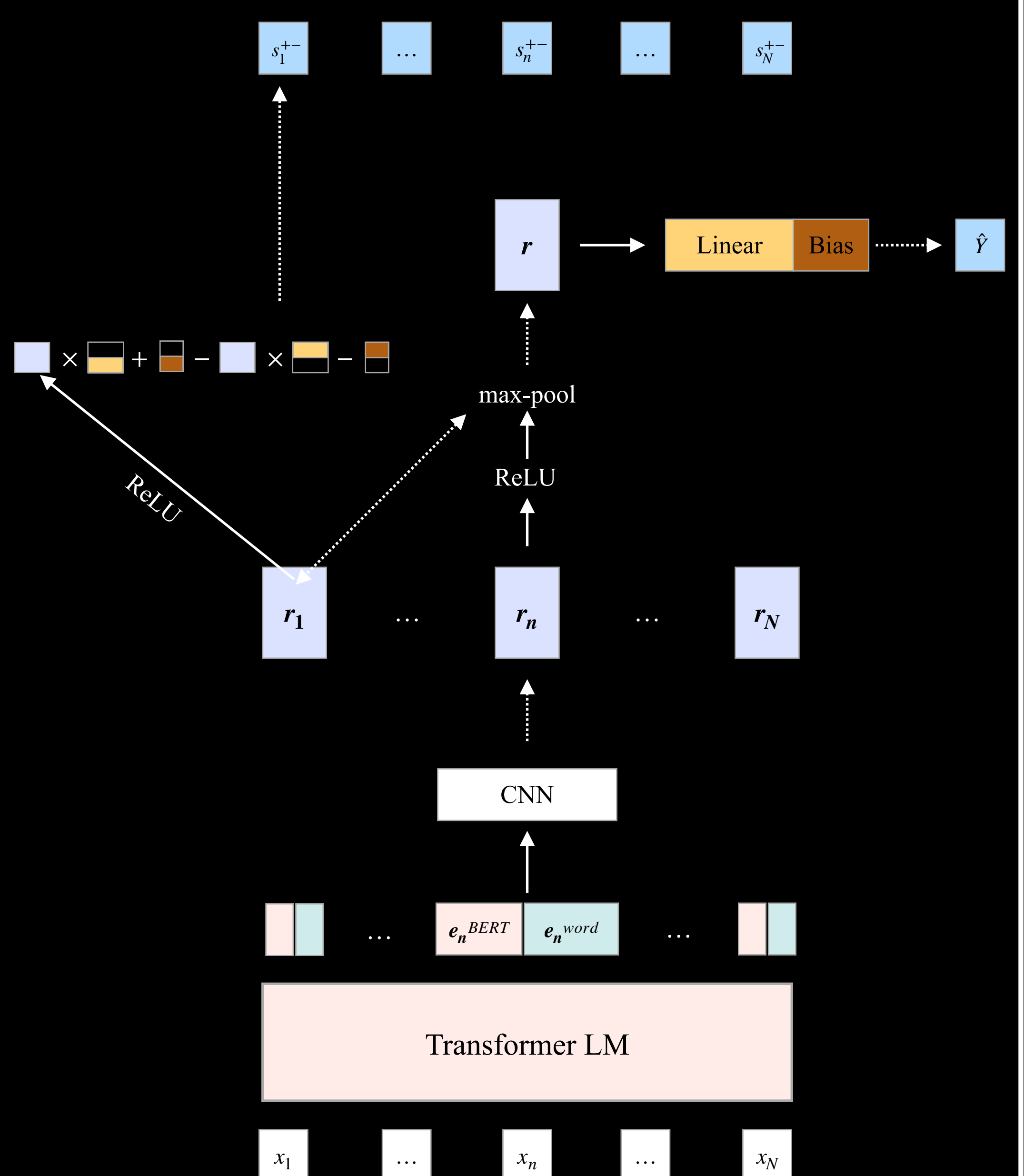
Model:
K-NN Approx. of Transformer ($BERT_{LARGE}$) +CNNDecomposition+MinMaxLoss

Model	Training set	Support set	$F_{0.5}$
K-NN Approx.	FCE	FCE	27.0
K-NN Approx.	FCE	FCE+OOD	46.3
Original Model	FCE	-	25.8
Original Model	FCE+OOD	-	33.3

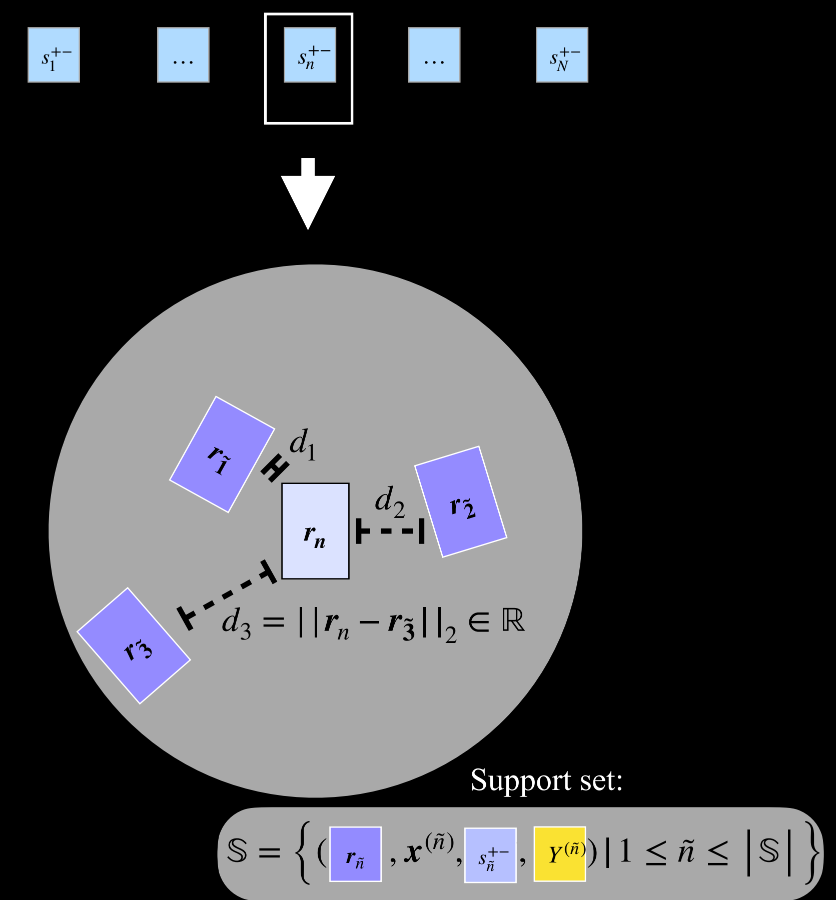
Token-level FCE+News2k (domain-shifted) test set results (Main text: Table 5)

Summary

Sequence Labeling via a Convolutional Decomposition



K-NN Approximation



$$s_n^{+-} \approx \beta + w_1 \cdot \left(\tanh(s_{\tilde{1}}^{+-}) + \gamma \cdot Y^{(\tilde{1})}\right) + w_2 \cdot \left(\tanh(s_{\tilde{2}}^{+-}) + \gamma \cdot Y^{(\tilde{2})}\right) + w_3 \cdot \left(\tanh(s_{\tilde{3}}^{+-}) + \gamma \cdot Y^{(\tilde{3})}\right)$$

$$w_k = \frac{\exp(-d_k/\tau)}{\sum_{k'=1}^{3} \exp(-d_{k'}/\tau)}$$

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Appendix

Presentation Appendix: *Parting Thoughts*

- Predictions from deep networks become more reliable as the following increase (potentially at expense of lower admitted N):
  - Closer distances to the support set ↓
  - Greater agreement between predictions and labels (i.e., stronger models, greater K-NN output magnitude) ↓
  - More labeled data at the desired resolution of analysis ↓

The decompositions described today provide a new means of analyzing and constraining the predictions against the data, yielding new levers for deploying and interpreting networks

More reliable predictions ⟵

Presentation Appendix: *Not Covered Today*

- Aggregate, comparative feature extraction/importance

$$\text{E.g., } \mathrm{ngram}^{-}_{\mathrm{n:n+(z-1)}} = \sum_{\mathrm{i=n}}^{\mathrm{n+(z-1)}} (\mathrm{s}_{\mathrm{i}}^{-} - \mathrm{b}_1)$$

- Decision rules

  E.g., only admit true positive matches:

$$\hat{y}_{N+1} = f(x_{N+1}) \cdot \left[f(x_{N+1}) = f(x_n) \wedge f(x_n) = y_n\right] + NULL \cdot \left[f(x_{N+1}) \neq f(x_n) \vee f(x_n) \neq y_n\right], \text{where } n = \underset{n \in \{1,\ldots,N\}}{\arg\min} \; ||r_n - r_{N+1}||_2$$

- Additional tasks and datasets, further illustrating:
  - Implications/juxtaposition of OOD robustness vs. detection and updatability
  - Ability to detect features for text analysis of large document sets

Presentation Appendix: Additional Considerations

- Alignment ("diagonally within sequence")

E.g., NLI & fact verification

  - Use bi-encoder, or masked cross-encoder, instead
- "Non-sparse" fully-supervised labeling for long sequences
  - Larger *M* makes dense search more expensive
  - If sparse feature detection not needed, can dispense with max-pool (& thus, the *horizontal* decomposition)

Can then proceed to use the K-NN model approximation as described today