



Look Both Ways and No Sink: Converting LLMs into Text Encoders without Training

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<https://github.com/bigai-nlco/NoSink.git>



1. Method

In **Low-Resource, Domain-Specific** scenarios, general representation models often fail due to limited domain data and domain gaps

⇒ A novel **Training-Free** conversion approach that significantly improves the performance of pretrained decoders in various domains!

Algorithm 1 Model Forward Pass

```
0: def forward(self, x = (x1, x2, ..., xT)):
0:   h = self.embedding(x) {Embed input sequence}
0:   for i, layer in enumerate(self.decoder_layers) do
0:     mask = self.get_mask(i) {Select Mask based on layer ID}
0:     h_attn = layer.attn(h, mask) {Self Attention layer}
0:     h_ffn = layer.ffn(h_attn) {Feed-forward layer}
0:     h = h + h_ffn {Residual connection}
0:   end for
0:   return self.head(h) {Generate output sequence} = 0
```

Attention Mask Types:

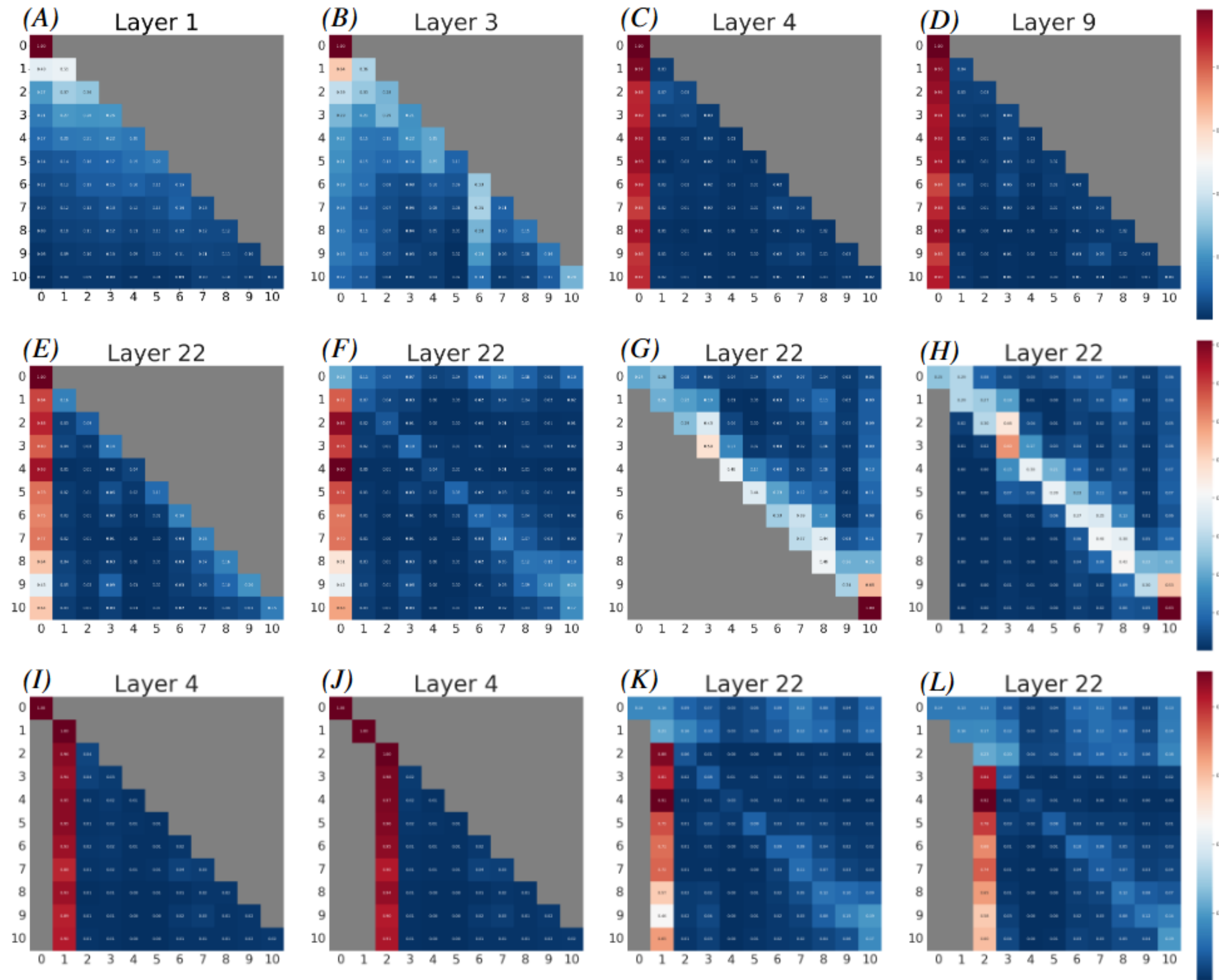
- **FWD**: standard causal mask.
- **BACK**: transpose of causal mask (each token attends to itself and subsequent).
- **BIDIR**: zero matrix (no masking).
- **NoSink-X**: X with the first column elements set to negative infinity.

Architecture Types: (assume the model has L layers)

- **INPLACE-BIDIR**: BIDIR if $i > L - k$; otherwise FWD.
- **INPLACE-BACK**: BACK if $i > L - k$; otherwise FWD.
- **MASK0-BIDIR**: NoSink-BIDIR if $i > L - k$; otherwise FWD.
- **MASK0-ALL**: NoSink-BIDIR if $i < L - k$; otherwise NoSink-FWD.
- **MASK0&BIDIR**: first FWD, then BIDIR, finally NoSink-BIDIR

3. Attention Map Visualization

Figure: (A)-(E) show attention score distributions in specific layers of a standard Transformer decoder. (F)-(H) display attention scores in the final layer with various masking methods. (I)-(K) demonstrate the attention sink shifting phenomenon, where masking initial tokens shifts the sink token to subsequent ones.



6. Experimental Results

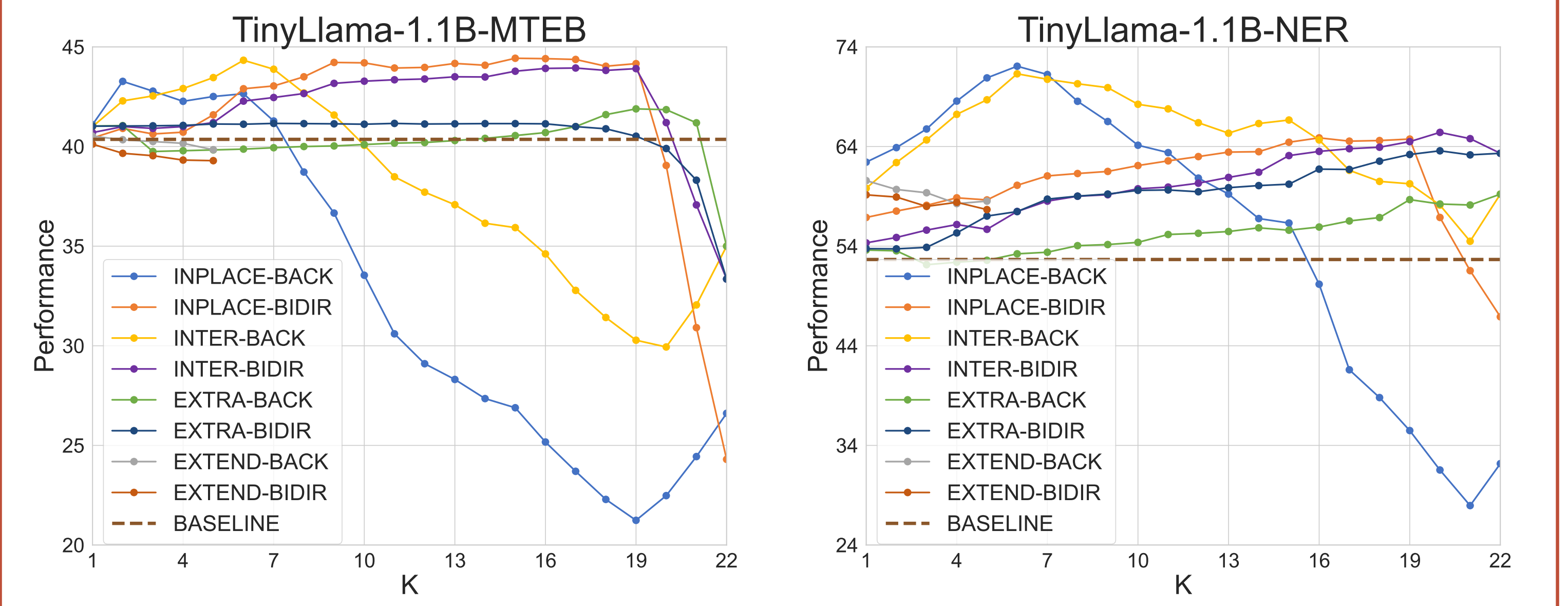
General	MTEB	CoNLL	AVG
BGE-M3	66.8	70.1	68.4
NV-Embed-V2	74.7	70.7	72.7
+MASK0&BIDIR	75.8	85.9	80.8
GTE-Qwen2-7B	70.9	71.5	71.2
+MASK0&BIDIR	74.1	80.2	77.2
E5-mistral	68.4	57.9	63.1
+INPLACE-BIDIR	70.9	74.8	72.9
+INTER-BACK	69.5	79.8	74.7
+MASK0-BIDIR	72.8	83.6	78.2
+MASK0&BIDIR	74.0	85.2	79.6

Finance	FIQA	FPB	NER	AVG
In-Context Learning	75.1	62.5	68.2	68.6
BGE-M3	81.0	94.2	68.2	81.3
FinBert	78.0	98.7	59.1	78.6
NV-Embed-V2	86.9	96.2	77.6	86.9
+MASK0&BIDIR	87.9	97.8	83.1	89.6
GTE-Qwen2-7B	83.3	95.8	67.6	82.2
+MASK0&BIDIR	85.0	97.6	81.3	88.0
Finma-7B	91.3	99.1	67.8	86.1
+INPLACE-BIDIR	93.2	99.1	69.6	87.3
+INTER-BACK	91.9	98.3	81.6	90.3
+MASK0-BIDIR	93.9	99.8	87.1	93.6
+MASK0&BIDIR	94.4	99.8	89.5	94.5

Medicine	PQAL	Chem	MQP	RCT	AVG
In-Context Learning	66.0	47.6	73.0	56.7	60.8
BGE-M3	63.0	68.9	77.7	69.8	69.9
MedicalBert	54.0	53.1	64.8	53.4	56.3
NV-Embed-V2	57.0	77.1	80.8	74.3	72.3
+MASK0&BIDIR	62.5	77.9	81.4	84.6	76.6
GTE-Qwen2-7B	56.2	78.0	77.7	77.1	72.3
+MASK0&BIDIR	63.0	77.9	78.8	82.9	75.7
BioMed-Llama	56.0	77.9	66.8	81.6	70.6
+INPLACE-BIDIR	59.0	78.4	73.4	82.5	73.3
+INTER-BACK	57.5	78.2	72.8	80.5	72.3
+MASK0-BIDIR	63.0	79.0	74.8	88.0	76.2
+MASK0&BIDIR	65.5	79.4	75.2	87.5	76.9

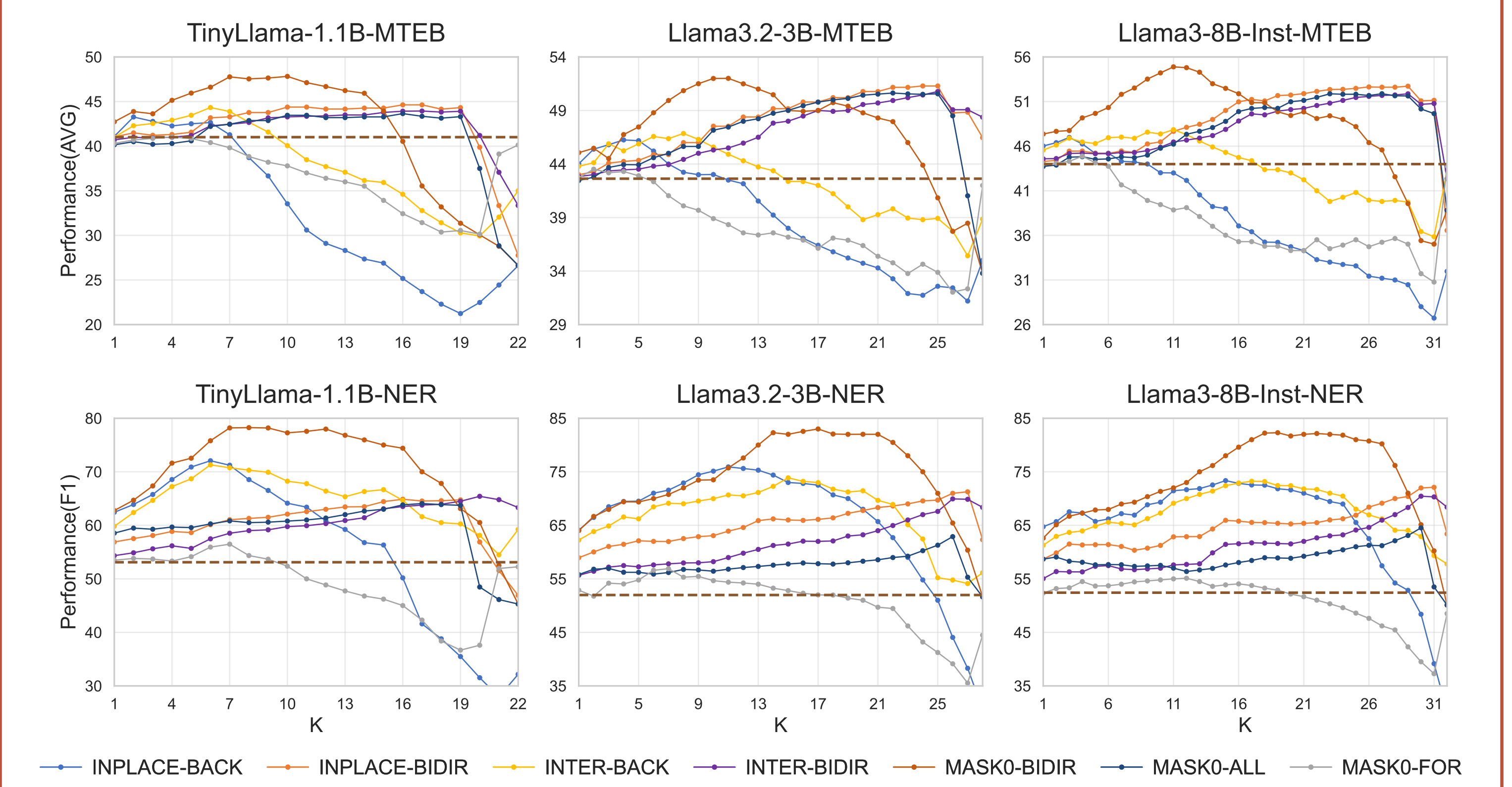
Law	SCOTUS		ToS	AVG
	mic-F1	mac-F1		
In-Context Learning	30.0	20.1	84.9	45.0
BGE-M3	68.4	46.8	84.7	66.6
InLegalBert	66.0	40.1	82.3	62.8
NV-Embed-V2	76.3	68.2	88.8	77.8
+MASK0&BIDIR	78.7	71.5	91.0	80.4
GTE-Qwen2-7B	73.9	62.6	89.1	75.2
+MASK0&BIDIR	77.3	69.9	91.5	79.6
LLama-Lawyer	73.7	61.1	89.7	74.8
+INPLACE-BIDIR	75.9	65.6	90.5	77.3
+INTER-BACK	74.1	64.6	90.3	76.3
+MASK0-BIDIR	75.9	65.6	90.7	77.4
+MASK0&BIDIR	76.8	66.0	91.5	78.1

2. Experimental Results



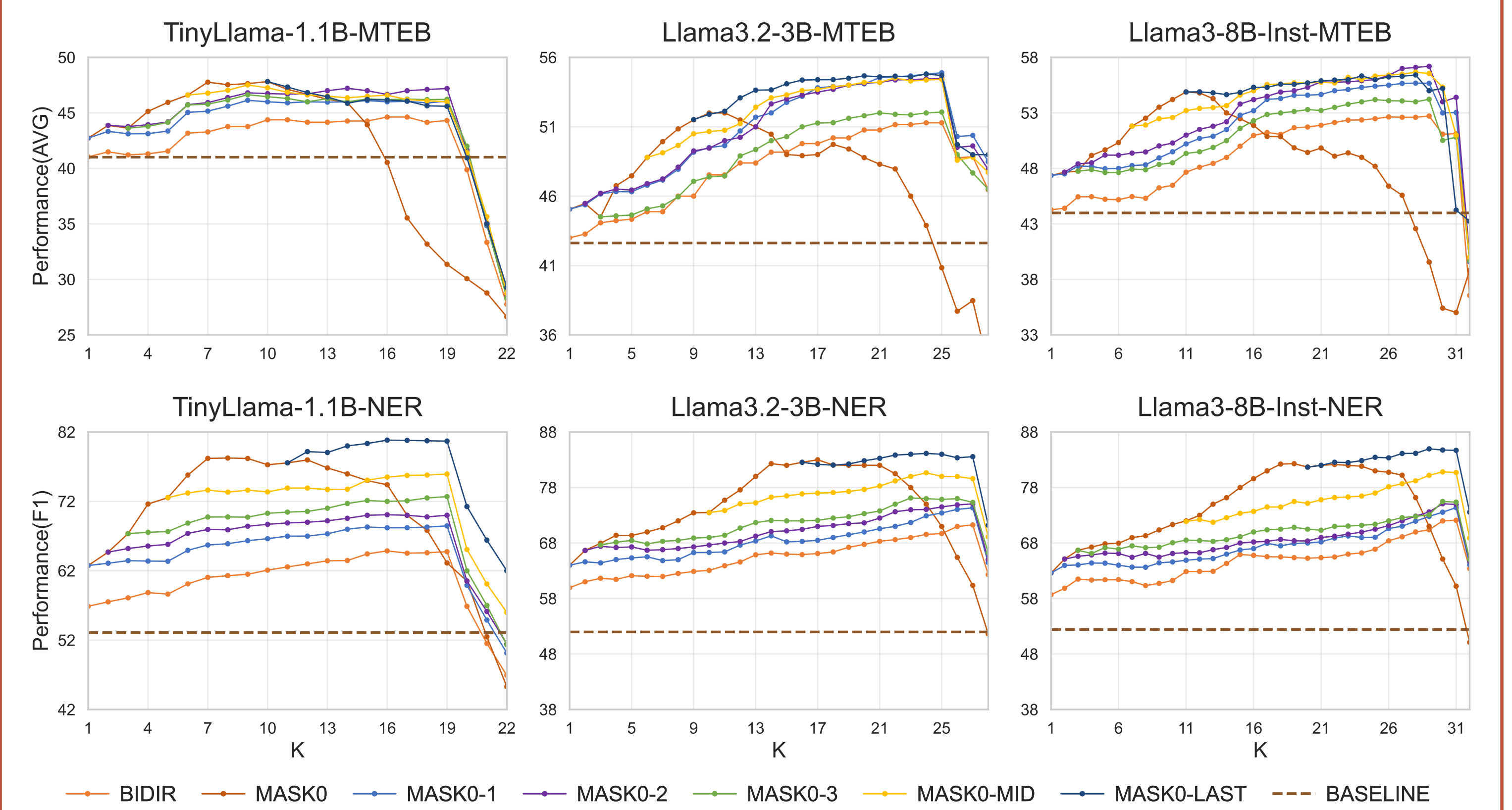
- **Maintaining some layers as FWD can be beneficial.**
- **INPLAC-BACK surpasses INPLACE-BIDIR when k is small.**

4. Experimental Results



- **MASK0-BIDIR achieves optimal performance by eliminating sinks.**
- **Note: directly masking the first token in all layers(MASK0-ALL) will not eliminate the sink!(see the last row of the score visualization on the left)**

5. Experimental Results



- **By combining the effectiveness of MASK0-BIDIR and the stability of INPLACE-BIDIR, MASK0&BIDIR can further enhance model performance.**